Smartphone Screen Time:
Self-reported estimates are inaccurate because mobile devices distort time perception

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A Dissertation submitted in fulfilment of the requirements for the award of the degree of Master of Art (Psychology)

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2020

COMPULSORY DECLARATION

This work has not been previously submitted in whole, or in part, for the award of any degree. It is my own work. Each significant contribution to, and quotation in, this dissertation from the work, or works, of other people has been attributed, and has been cited and referenced.

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Acknowledgement

I would like to express my sincerest gratitude to the following people for their support and contribution to this work:

First and foremost, I would like to thank my supervisor, Professor Kevin Thomas. Without all your help, knowledge, guidance, and support this thesis would not have been possible. Thank you for all the meetings, meticulous edits, support, and patience.

Second, to the Cyberpsychology small group, Lauren Gardner, Diaan Mynhardt, Jessica Oosthuizen, Jenny Pan, and Savannah Reichardt. Thank you for your thoughtful input and feedback throughout the research process, and thank you for keeping me motivated during our weekly meetings.

Last, to my family, boyfriend, and friends (especially Allie McHale!). Thank you for all the support, love, encouragement, and draft-edits throughout this process. I cannot emphasize how much all this support meant to me throughout this process.

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List of Abbreviations

ANOVA	Analysis of Variance
BDI-II	Beck Depression Inventory-Second Edition
BUS	Battery Use Screenshot
CI	Confidence Interval
COVID-19	Corona Virus Disease
DSA	Department of Student Affairs
DSM	Diagnostic and Statistical Manual of Mental Health
ESE	Effect Size Estimate
HR	Heart Rate
iOS	iPhone Operating System
iOS STT	iPhone Screen Time Tracker
LL	Lower Limit
MAQ	Mobile Attachment Questionnaire
NEO-FFI-R	NEO Five Factor Inventory-Revised
SNS	Sympathetic Nervous Systems
SPSS	Statistical Package for the Social Sciences
SRPP	Student Research Particpation Programme
STAI	State-Trait Anxiety Inventory
UL	Upper Limit
UCT	University of Cape Town

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Abstract

Cyberpsychological research aims to understand the increasingly prevalent human-smartphone interaction. Investigation of factors influencing screen time (i.e., the amount of time spent actively using the device) is a core element of this research. This thesis presents two studies investigating associations between smartphone screen time and subjective time perception. Study 1 compared differences between self-reported and objective screen time in a sample of undergraduate students. It also investigated the influence of individual difference factors, and COVID-19 lockdown restrictions, on screen time. Participants (N = 267, 18–25 years) completed scales measuring depression, anxiety, and smartphone attachment, and estimated their screen time. Thereafter, they sent screenshots of their screen time as measured automatically by their iPhone software. Some (n = 24) shared that objective data again during the COVID-19 lockdown. Self-reports either underestimated actual use (when screen time was objectively tracked over 10 days, including two weekends; $p < .001$). or overestimated it (when it was tracked over 7 days only; $p = .010$.). Use was heavier over weekends and screen time increased significantly during the lockdown ($p = .001$). Finally, smartphone attachment mediated the relationship between objective screen time and depression. Study 1 concluded that iPhone tracking features can reliably collect objective screen time data, and that screen time is significantly influenced by both individual difference factors and environmental context. Study 2 aimed to understand the mechanisms underlying differences between objective and subjective screen time estimates. The time-emotion paradox proposes that emotional conditions affect time perception. Because, subjectively, smartphones are pleasure providing and anxiety-alleviating devices, previous research suggests they might facilitate time distortion. To test whether time spent using a smartphone will feel shorter while time without it will feel longer, we assigned participants (N = 55; 18–25 years) to either a Smartphone Present or a Smartphone Absent condition and then had them wait alone while being video recorded and having their heart rate monitored. After 13.5 minutes, they estimated the waiting period's duration. As predicted, all Smartphone Present participants used their devices during the waiting period and significantly underestimated its duration, $p < .001$. Unexpectedly, Smartphone Absent participants also underestimated the duration, $p < .001$, and were no more anxious than Smartphone Present participants, $ps > .550$. However, Smartphone Absent participants showed more signs of both boredom and productivity, $ps < .042$. Hence, it appears those participants found engaging ways to occupy themselves, thus facilitating their time underestimations. Study 2 concluded that although smartphone use was

apparently so pleasant that it distorted time perception, smartphone absence was not so aversive as to distort it in the opposite direction.

Chapter One:
General Introduction

One of the main aims of cyberpsychology, a recently-developed sub-discipline of psychology, is to understand the everyday interactions between humans and computerized devices (Connolly et al., 2016). Increasingly, the focus of this research is on the relationships people have with their smartphones. A primary reason for this increased focus is that, over the past decade, smartphones have become embedded in everyday life. Current statistics suggest there are 2.71 billion smartphone users; in other words, one of every three people in the world owns such a device (Deyan, 2019). This proliferation has arisen in part because competition among smartphone manufacturers (e.g., Apple, Samsung, Huawei) has been a boon for consumers: The devices have become accessible and affordable for almost everyone. In South Africa, smartphones are so ubiquitous that the once-prominent 'digital divide' between individuals from different socioeconomic strata has practically disappeared (de Jager & Van Belle, 2014; Swanepoel & Thomas, 2012).

A major reason for the popularity and widespread use of these devices is that their functional abilities enhance daily life by simplifying tasks (e.g., they commonly include mapping and calendar applications), by facilitating widespread communication (e.g., via messaging applications), by enabling easy access to information (e.g., via web browsers), and by providing forms of recreation (e.g., via gaming and music applications; see, e.g., Ahn & Jung, 2014; Fullwood et al., 2017). Hence, everyday life might be significantly poorer and less pleasant without the presence of smartphones.

Research on the human-smartphone interaction is heavily influenced by psychological concepts whose origin is elsewhere in the field. For instance, the concept of *addiction* is borrowed from clinical psychology, and numerous cyberpsychological studies have attempted to identify personality traits and individual difference factors associated with smartphone addiction (see, e.g., Pearson & Hussain, 2015; Thompson & Thompson, 2017). The concept of *attachment* is borrowed from developmental psychology, and numerous cyberpsychological studies have attempted to describe ways in which degree of smartphone attachment is affected by individual differences and, in turn, affects anxiety (see, e.g., Cheever et al., 2014; Konok et al., 2016; Konok et al., 2017; Meschtscherjakov et al., 2014). The concept of *psychological wellbeing* (e.g., life satisfaction, self-acceptance, and autonomy; Ryff & Keyes, 1995) is borrowed from health psychology, and cyberpsychological research has attempted to outline ways in which excessive smartphone use is associated with inferior quality of life (see, e.g., Twenge et al., 2018).

Regardless of the exact focus of the research, or from which other areas of psychological inquiry key concepts are borrowed, a core element of investigation into the human-smartphone interaction is quantification of screen time (i.e., the amount of time that one spends actively using one's device). Although most previous cyberpsychological research has focused on consequences of extended screen time, this Master's thesis presents research investigating associations between smartphone screen time and subjective time perception. Specifically, Study 1 compared differences between self-reported and objective screen time in a sample of South African university students. Study 2 aimed to assess whether a similar sample of students accurately estimated the duration of a waiting situation when they were left with or without their smartphone in their possession.

In summary, the primary focus of this thesis is on subjective estimation of screen time, individual difference and contextual factors that might affect these estimations, and whether active engagement with one's smartphone distorts subjective time perception. Chapter 2 presents a brief review of the literature relevant to those topics. Chapter 3 presents Study 1, titled *Smartphone Screen Time: Inaccuracy of self-reports and influence of psychological and contextual factors*. Chapter 4 presents Study 2, titled *Smartphones and Time Distortion: Does presence of mobile devices influence time perception?*. Chapter 5 concludes the thesis by presenting a general discussion that summarizes the overall results and conclusions, considers limitations of the research program, offers thoughts on some wider implications of the findings, and recommends directions for future research.

Chapter Two:
Literature Review

The human-smartphone interaction has become a primary focus of cyberpsychological research. One reason for this intense focus is that the smartphone is one of the most globally prevalent and sought-after objects in contemporary society. The fact that the smartphone is a handheld device that features advanced computational power makes it a convenient and important tool for business, school, and recreational purposes.

Research into human-smartphone interactions is, broadly speaking, dominated by two opposing schools of thought. One takes the position that smartphone use is associated with poor mental and physical health outcomes, whereas the other suggests that the devices help people navigate through everyday activities more effectively and efficiently, and therefore have the potential to enhance wellbeing.

This review is structured as follows: The first major section introduces a fundamental generational distinction in the digital world. This distinction is important to consider before reviewing the specifically relevant cyberpsychological literature. The second major section reviews literature suggesting that smartphones are problematic. This literature emerges from the notion that there has been, and continues to be, both individual and societal needs to adjust to these devices, and that this adjustment has not always been successful. The third major section reviews literature suggesting that smartphones have the potential to enhance everyday life. The fourth major section contains a discussion of measurement issues associated with self-reported smartphone screen time estimates. I then discuss how time distortion may be an explanation for why these self-report estimates may be inaccurate. Finally, I review the literature on smartphone attachment, and discuss experiments that have measured this concept. The chapter concludes with a summary statement of the way in which previous research provides a rationale for conducting the current study.

Generational Differences: Digital natives versus digital immigrants

There is a key distinction between the generation of people who have grown up with smartphones versus the generation that has had to learn to adapt to smartphone use. Prensky (2001) coined the term ‘digital native’ to refer to the former group and the term ‘digital immigrants’ to refer to the latter. Formally speaking, then, the term *digital natives* refers to individuals who were born after the widespread adoption of mobile technology. These individuals have grown up accustomed to the pervasive presence of mobile technology, and have habituated to the various benefits that smartphones enable. Additionally, smartphones have facilitated some (if not a large majority) of this generation’s social interactions. In contrast, the term *digital immigrants* refers to individuals who were born before the widespread adoption of digital devices and who have had to adjust to a life that features the pervasive use of handheld devices (e.g., to facilitate new forms of communication, socializing, and/or working).

Prensky (2001) draws on several examples to illustrate the essence of the digital divide that separates these two groups. There are, for instance, differences in information processing (e.g., digital immigrants prefer to print out documents before reading and editing them, whereas digital natives are more comfortable reading and editing documents on computers or handheld devices) and in information sharing (e.g., where digital immigrants might prefer to invite people into their office to share an online video, digital natives are more likely to email or WhatsApp the link to the video).

More recently, other researchers have reported that these generational differences are expressed via different attitudes to smartphones (e.g., digital immigrants believe that gaming abilities lead to addiction, whereas digital immigrants believe that the portability of smartphones lead to addiction; Ahn & Jung, 2014) and different levels of dependence on the devices (e.g., digital natives are more dependent on smartphones to socialize than digital immigrants are; Hodes et al., 2020).

Because most research on human-smartphone interactions focuses primarily on digital natives, the review below concerns itself mostly with that segment of the population.

Research Highlighting Negative Impacts of Smartphone Use

Historically, a large body of cyberpsychological research has focused on the negative impacts that smartphones can have on individual mental and physical health. This research suggests that high levels of smartphone use/screen time are associated with (a) decreased psychological wellbeing (see, e.g., Przybylski & Weinstein, 2019; Twenge et al., 2018); (b) decreased sleep quantity (see, e.g., Christensen et al., 2016; Garmy et al., 2018; Hale & Guan, 2015); (c) increased body adiposity and sedentary behavior (see, e.g., Costigan et al., 2013; Stiglic & Viner, 2019); (d) poor academic performance (see, e.g., Froese et al., 2012; Lepp et al., 2014); (e) increased loneliness (see, e.g., Enez Darcin et al., 2016; Jiang et al., 2018); and (f) decreased cognitive capacities when the device is present (i.e., the mere presence of a smartphone acts as a distractor; Thornton et al., 2014; Ward et al., 2017).

A fundamental aspect of the research problematizing smartphone use is the suggestion that the concept of *smartphone addiction* exists as a viable psychological construct. A specific proposal is that smartphone addiction is similar to Internet addiction, which has been added as a formal diagnostic term to DSM-5 (American Psychiatric Association, 2013).

Hence, smartphone addiction would entail: (1) compulsive behavior and/or overuse; (2) functional impairment due to the extent of use (e.g., sleep disturbances, or difficulty concentrating at school or work); (3) experiences of withdrawal-type symptoms when the smartphone is not available for use; (4) tolerance (i.e., needing to use the device more and more frequently in order to derive the same pleasure from it); and (5) positive anticipation (e.g., the expectation that using a smartphone will relieve stress or alleviate anxiety; see, e.g., Horvath et al., 2020; Kwon et al., 2013; Lin et al., 2014). Relatedly, the term *nomophobia (no-mobile-phobia)* has been coined to describe the fear of being without one's mobile/smartphone (King et al., 2013; Yildirim & Correia, 2015).

Consistent with this school of thought are numerous studies suggesting that heavy smartphone use is associated with poor mental health outcomes (most commonly, depression and anxiety; see, e.g., Boers et al., 2019; Demirci et al., 2015; Hussain et al., 2017; Lepp et al., 2014; Stiglic & Viner, 2019). For example, Boumosleh and Jaalouk (2017) reported that in their large Lebanese undergraduate student sample ($N = 688$; $M_{age} = 20.64 \pm 1.88$ years) depression (as measured by Patient Health Questionnaire-2; Kroenke et al., 2003) and anxiety (as measured by the Generalized Anxiety Disorder-2; Spitzer et al., 2006) scores were independent positive predictors of smartphone addiction (as measured by the Smartphone Addiction Inventory; Lin et al., 2014).

Emerging research suggests that heavy smartphone use, per se, is not necessarily associated with increased levels of depression and anxiety. This more nuanced body of research proposes instead that heavy use of certain applications, and/or certain types of smartphone use, are associated with the negative mental health outcomes described by earlier studies. For instance, Panova and Lleras (2016) found that, in their sample of American undergraduates ($N = 84$), using a smartphone to alleviate boredom was not associated with anxiety and depression. Similarly, Elhai et al. (2017) found, in their cross-national sample ($N = 308$ individuals recruited via Amazon Turk), that social smartphone use (e.g., messaging) was not associated with increased depression and anxiety whereas non-social use (e.g., reading the news) was.

Consistent with these latter findings are data indicating that mere frequency of use (especially subjectively estimated use) is not significantly associated with poor mental health outcomes (see, e.g., Rozgonjuk et al., 2020). For instance, Shaw et al. (2020) reported that self-report measures of screen time (as compared to objective log data) inflated the magnitude of association between screen time and mental health outcomes (depression, anxiety, and stress). Similarly, Rozgonjuk et al. (2018) reported no significant association between objective screen time data and symptoms of depression and anxiety.

It is important to note that most studies in this literature on problematic outcomes associated with smartphone use are of cross-sectional and correlational design. Hence, it is difficult to ascertain the direction of causation (i.e., was it the smartphone that caused these problems or did these problems exist before the individual's contact with the device?). Future studies employing experimental designs will be able to better clarify not only these directions but also mechanisms underlying the associations and risk/protective factors affecting the magnitude of effects.

Research Highlighting Positive Impacts of Smartphone Use

Research on this side of the field aims to move away from the deviance discourse (i.e., away from problematizing smartphones) and instead accepts the pervasive and persistent presence of these devices. In other words, the tack taken here is that it is more beneficial to avoid focusing on the addiction rhetoric that aims to pathologize smartphone use because these devices are not going to disappear and individuals are not going to stop using them voluntarily (Panova & Carbonell, 2018).

Of vital importance to this area of the research are attempts to understand what smartphones mean to individuals (and, specifically, to digital natives). Reports from qualitative studies suggest that smartphones are "friend-like", alleviate boredom, provide recreation, facilitate access to widespread information, and enable communication (Fullwood et al., 2017, p. 350; Jung, 2014). Of course, smartphones also have many functional benefits that enhance daily life (e.g., instant messaging, Internet banking, online shopping).

Research in this area also describes how specific applications might help address particular health-related issues. For example, there is promising positive evidence for applications that assist in medication adherence (see, e.g., Dayer et al., 2013), that promote physical activity (see, e.g., Romeo et al., 2019), and that guide dietary and nutrition requirements for athletes (see, e.g., Jospe et al., 2015). There are also suggestions that smartphone applications might be effective at improving socialization and emotion recognition in children diagnosed with autism spectrum disorders (see, e.g., Lamm et al., 2014).

Because smartphones offer all these potential benefits, it is clear that people are not simply going to choose to stop using them. Moreover, in some instances (e.g., when businesses require their employees to be accessible online, or when students are taking online classes) individuals cannot afford to remove themselves voluntarily from the digital world.

Finally, and importantly, smartphone manufacturers will not remove their product from the market when there is clearly a high demand for it.

Subjective Estimates and Objective Measures of Smartphone Screen Time

A key concept in studying smartphones is the quantification of screen time (i.e., the amount of time that one spends actively using one's device). Most previous research has used self-report estimates to measure screen time. However, numerous studies of various aspects of human psychology suggest that people do not report accurately on their own behavioral patterns (see, e.g., Auer & Griffiths, 2017; Chastin et al., 2018). For example, Lipinska and Thomas (2017) found significant discrepancies between subjective and objective measures of time spent sleeping. Similarly, studies using computer and television tracking technology suggest that individuals significantly underestimate the amount of time they spend watching television and browsing Facebook (Junco, 2013; Otten et al., 2010). Hence, conclusions drawn from research that relies solely on self-reported screen time must be subject to serious critical inquiry.

In studies that specifically assessed the validity of self-report smartphone use, Lin and colleagues (2015; $N = 79$, $M_{age} = 22.4 \pm 2.3$ years) and Felisoni and Godoi (2018; $N = 43$ undergraduates) both reported that young adults significantly *underestimated* (verified by objective data gathered by a tracking application) the amount of time they spent using their smartphones. On the other hand, Kobayashi and Boase (2012) reported that their adult participants ($N = 310$, age range = 20–69 years) significantly *overestimated* (again, relative to objective data gathered by a tracking application) the amount of time they spent using their smartphones. Studies using phone bills as objective criteria also report finding subjective *overestimates* of time spent using cell phones (Boase & Ling, 2013; Shum et al., 2011).

Studies using the aforementioned tracking applications have some significant limitations. For instance, these applications do not track activity if the smartphone is set in airplane mode (see Christensen et al., 2016). Moreover, researchers often request that participants download the applications onto their smartphones after completing baseline measures that explicitly ask about smartphone use and/or activity (e.g., Andrews et al., 2015; Felisoni & Godoi, 2018; Kobayashi & Boase, 2012; Lee et al., 2017; Lin et al., 2015; Rahmati & Zhong, 2012; Shaw et al., 2020). Hence, these participants may be aware that their screen time is being monitored, and this awareness may lead to particular behavioral changes. More specifically, the Hawthorne effect (Landsberger, 1957) may occur: If one knows one's screen time is being tracked, one might change one's behavior to match what one thinks the researcher desires (e.g., by curbing excessive use of the device, or by changing usage patterns to fit a more socially desirable narrative).

Recent advances in the iPhone operating system (iOS) and associated software offer a potential solution to help study designs mitigate this threat to internal validity. Specifically, these advances introduced (a) a Battery Use tracker that monitors iPhone usage over 10 days, and (b) a Screen Time function that monitors iPhone usage over 7 days (*Set screen time, allowances, and limits on iPhone*, 2019). Each of these trackers presents information about the total number of hours and minutes the phone has been used over the period under consideration, as well as the amount of time spent on each application over that period. Unlike some other screen time trackers, iOS software records activity whenever the smartphone is switched on (i.e., even when it is in airplane mode). However, the Battery Use tracker distinguishes active from passive use (i.e., time spent actively using one's smartphone versus background activity). To facilitate the generation of the Screen Time reports, the user must activate the feature. In contrast, Battery Use tracking is automatic as long as the smartphone is equipped with at least the iOS 8 update.

It is also important to note a significant consequence of the different periods monitored by these two trackers: Whereas 7 days will only include one weekend, 10 days can include two weekends, and weekend versus weekday screen-time patterns may vary due to changing work demands and/or class schedules. For example, Yang et al. (2018) reported that, in a sample of adolescent students ($N = 218$, $M_{\text{age}} = 18.23 \pm 0.91$ years), those who self-identified as heavy smartphone users (i.e., more than 3 hours use daily) reported higher use on the weekend than on weekdays (but see Wilcockson et al., 2018, for contrasting data). Similarly, Fullwood et al. (2017) reported that their undergraduate participants ($N = 18$; $M_{age} = 25.9$ years) suggested that context determines their smartphone usage (e.g., one might spend more time on one's smartphone when alone at home compared to when one is out). Other research has suggested that location can influence smartphone use (Rahmati & Zhong, 2012).

Nevertheless, studies using these iOS advances have demonstrated that they can be useful research tools. Gower and Moreno (2018) reported that asking their American participants ($N = 1156$; $M_{age} = 13.6 \pm 1.09$ years; age range = 12–15 years) for a screen shot of their Battery Use tracker was a viable and feasible way to collect real-time and unbiased screen time data. Ellis et al. (2019) reported that in their British sample iPhone screen time reports had weak correlations with smartphone addiction scales (e.g., $r = .27$ in correlation with the Problematic Mobile Phone Use Questionnaire; Billieux et al., 2008) and with smartphone usage scales (e.g., $r = .34$ in correlation with the Smartphone Use Questionnaire [General]; Marty-Dugas et al., 2018).

Interestingly, Ellis et al. also reported that the correlation between self-reported smartphone use and objective screen time was stronger than that between other smartphone use scales and objective screen time, but was still fairly weak ($r = .48$) and did not justify the reliability of self-reported screen time (see Lee et al., 2017, for similar data). The authors did not provide more information about whether their participants underestimated or overestimated their screen time, however.

Smartphone Use and Time Distortion

Lin et al. (2015) posited a potential explanation for why individuals may incorrectly estimate (i.e., underestimate or overestimate) their screen time. Specifically, their proposition was that excessive screen time enables a sense of time distortion (i.e., that one loses track of time when one spends long periods on a smartphone, so that, for instance, spending an hour on the device can feel like one has spent 20 minutes). Hence, the experience of time distortion might explain discrepancies between subjective estimates and objective measures of screen time.

More generally speaking, time perception is heavily influenced by the pleasantness of a situation. The term “time-emotion paradox” (Droit-Volet & Gil, 2009, p. 1943) has been coined to explain this phenomenon. It suggests that an individual’s emotional state affects how that person perceives time (i.e., negative emotions result in the passage of time feeling longer, whereas positive emotions make the passage of time feel shorter). Previous research has suggested that (a) the subjective experience of time feels shorter when individuals are exposed to pleasant music versus unpleasant music, even though objectively exposure is of the same duration (Droit-Volet et al., 2013; Noulhiane et al., 2007); and (b) students who experience higher levels of psychological distress (e.g., worry, anxiety, and other negative emotions) while anticipating their exam results feel that time is moving more slowly as they wait (Rankin et al., 2019). More germane to the research presented in this thesis is the finding that both novice and professional gamers report that a break interval between gaming subjectively feels longer than it is (i.e., the break is considered aversive because they were restrained from pleasant experience of playing; Rau et al., 2006).

The time-emotion paradox provides a potential explanation for underestimations of smartphone screen time (see, e.g., Felisoni & Godoi, 2018; Lin et al., 2015). Because many people report that smartphone use is a positive experience (i.e., that the devices provide a form of recreation and a sense of confidence, and that they alleviate boredom; Fullwood et al., 2017; Jung, 2014), the time-emotion paradox might predict that they would subjectively underestimate the amount of time they spend using these devices.

Additionally, because digital natives are so accustomed to the pervasive presence of smartphones it is reasonable to suggest that they use their devices without even acknowledging them (e.g., briefly checking a message when driving or picking up and looking at the phone during a social interaction). One might argue, then, that because smartphone use has become so habitual individuals may lose track of time when they are engaged with their devices (Felisoni & Godoi, 2018; Shaw et al., 2018). Of note, however, is a related body of literature suggesting that because digital natives are so accustomed to the device's pervasive presence they may subjectively overestimate their screen time (see, e.g., Boase & Ling, 2013; Shum et al., 2011) because they cannot imagine functioning without their smartphones (Ahn & Jung, 2014).

Smartphone Attachment

Smartphone attachment (or, more generally, mobile attachment) is a key concept when studying smartphone use (particularly that of digital natives). This concept refers to the emotional attachment that an individual has to their device (Konok et al., 2016; Meschtscherjakov et al., 2014). In defining the concept, cyberpsychologists draw on classical infant attachment theory, which suggests that an infant's attachment to its primary caregiver can be either secure, anxious-resistant, or anxious-avoidant (Bowlby, 1958). A secure attachment style is characterized by the infant being able to tolerate separation from the caregiver and being comfortable with venturing from the safe haven that the caregiver provides; this is considered a healthy attachment. An anxious-resistant attachment style is characterized by the infant being anxious about being separated from their caregiver and being anxious to explore beyond the safe haven the caregiver provides. Finally, an anxious-avoidant attachment style is characterized by the child relying on the caregiver, but also expecting to be rejected constantly (Ainsworth, 1989; Ainsworth & Bell, 1970; Bowlby, 1988)

Of particular interest here is that these attachment styles (a) persist into adulthood and extend to other relationships (see, e.g., Ammaniti et al., 2000; Bartholomew & Horowits, 1991), and (b) can extend to material objects (see, e.g., Bell & Spikins, 2018; Gjersoe et al., 2015). Hence, because smartphones are among the most prevalent and sought-after objects in contemporary society, the cyberpsychological literature has applied the classical developmental psychology theory in an attempt to characterize and define ways in which people might form emotional attachments to their mobile devices. Cyberpsychologists suggest that smartphone attachment includes the following components: (1) separation insecurity and separation anxiety (e.g., feeling anxious if one leaves one's phone at home or if the phone's battery dies), and (2) safe haven, and secure base (e.g., feeling more confident and comfortable when one's smartphone is present and/or using it to ease tension; Konok et al., 2016; Meschtscherjakov et al., 2014). Hence, at some levels of smartphone attachment separation does not cause distress (signifying a healthy secure attachment), whereas at other levels it does (signifying an unhealthy anxious attachment).

Assessing Smartphone Attachment: Responses to mobile separation

Developmental psychology researchers use a classic experimental paradigm, the strange situation scenario, to assess infant attachment. In this scenario, the infant's primary caregiver leaves them alone in a room. Researchers observe the infant's reaction to being alone and their response to the caregiver's subsequent return (see, e.g., Ainsworth & Bell, 1970; Van Rosmalen et al., 2015). Cyberpsychological researchers have adopted a similar scenario to assess individual levels of smartphone attachment. For example, Konok et al. (2017) placed participants' phones in a locked cabinet and left them to wait alone in a room for 3.5 minutes, under a research-related pretext. They reported that, in their sample (N = 93 Hungarian university students; median age = 21 years; age range = 18–26 years), participants exhibited seeking behaviors towards where their smartphone was stored, but showed no significant increases in self-reported anxiety (as measured by the State-Trait Anxiety Inventory State form [STAI-S]; Spielberger et al., 1983) or in heart rate measures.

In contrast, Cheever et al. (2014) reported that, in their sample (N = 122 university students; M_{age} = 24.40 ± 6.10 years; age range = 19–57 years), participants who were forced to wait in a large-group situation without their devices in their possession were significantly more anxious (as measured by the STAI-S) than those who kept their device in their possession but who were not allowed to use it. Similarly, Hartanto and Yang (2016) reported that, in their sample (N = 87 Singaporean undergraduates; M_{age} = 21.60 ± 2.11 years), participants showed significant increases in anxiety (as measured by the STAI-S) when separated from their ringing smartphone. Clayton et al. (2015) also reported that, in their sample (N = 41 American university students; M_{age} = 21.21 ± 3.78 years), participants reported significant increases in both self-report (measured by STAI-S) and objective (heart rate and galvanic skin response) measures of anxiety when separated from their ringing smartphone. Similar studies that include qualitative accounts report that participants describe their smartphone as a "security blanket" (Panova & Lleras, 2016, p. 255; see also Fullwood et al., 2017; Smetaniuk, 2014)

In summary, the extant literature suggests that smartphone attachment is similar to infant attachment: Separation from the attachment figure causes considerable anxiety and individuals seek proximity toward that figure when there is separation.

Assessing Smartphone Attachment: Behavior in the presence of the device

Few published studies have focused solely on individual behavioral responses to a waiting situation where the device remains in the individual's possession and they are allowed to use it freely. Brown et al. (2016) reported that 76% of their participants (N = 126; M_{age} = 18.79 ± 0.99 years) used their smartphones when left in a 5-min waiting situation with a close friend. They therefore concluded that the typical response of a digital native to a waiting situation is to use their smartphone. Rieger et al. (2017) reported that (a) almost half their student sample (22 of 45; M_{age} = 25.22 ± 6.90 years) used their mobile devices during a 10-min solo waiting period, and (b) contrary to their hypotheses, smartphone use during the waiting period did not induce a sense of relaxation or alleviate stress in their sample. In contrast, Panova and Lleras (2016) reported that during a 10-min solo waiting situation that followed directly after an laboratory-based stress-induction procedure, participants in their undergraduate sample (N = 84) who were allowed to maintain proximity to their smartphones reported being less anxious (as measured by the STAI-S) than participants in two other groups (viz., those who were allowed access to a computer and those who were left with no devices).

In summary, the few studies reporting on individual behavioral responses during a waiting situation within which participants are allowed to use their smartphones report contradictory findings. More research is needed to investigate questions such as whether the presence of a smartphone will alleviate the anxiety associated with a waiting period (as one might hypothesize based on basic smartphone attachment theory).

Associations between Smartphone Attachment and Screen Time

Some studies in the small literature exploring such associations suggest that smartphone use is significantly associated with dependence on, or attachment to, the device (see, e.g., Konok et al., 2016; Lee et al., 2014). For instance, Bae (2017) reported that in their school student sample (N = 2212 Koreans students; age range = 13–18 years) that smartphone use as a whole and various types of smartphone use (i.e., for information, entertainment, or gaming) were significantly associated with dependence on the device (as measured by the S Scale; National Information Society Agency, 2015). A plausible explanation for the presence of such an association is that many digital natives may use their device frequently and may also be nervous and anxious without it in close proximity.

However, one recent study reported that frequent or heavy smartphone use is not necessarily synonymous with a high degree of attachment to the device. Hodes et al. (2020) observed that young adults (*n* = 104; age range = 18–25 years) self-reported lower levels of use but higher levels of attachment whereas older adults (*n* = 117; age range = 30–60 years) self-reported higher levels of use but lower levels of attachment. Although it seems intuitive that the personal dependence and reliance an individual has on their smartphone should influence the amount of time they estimate spending on the device, it seems possible that one can present with higher use (e.g., due to work demands) but lower attachment (i.e., because being without the device does not cause anxiety).

One possible explanation for the contrast between the findings of Hodes et al. and others in this literature comes from emerging research suggesting that individuals are attached to the affordances that smartphones provide rather than to the device itself (i.e., the device is simply the material object that enables individuals to access vast amounts of information, entertainment, and socialization opportunities; Nie et al., 2020).

Overall Aims and Rationale

The literature reviewed above suggests that, although smartphones are among the most ubiquitous and desired possessions in contemporary society, our understanding of their effects on human behavior remain incomplete. A basic building block in improving such understanding is a reliable measure of screen time (i.e., the amount of time that one spends actively using one's device). Recent updates to the iPhone operating system provide a potential solution to the problem of easy access to unbiased and reliable screen time data. With these data in hand, one might begin to answer questions (raised but not resolved by previously published studies) about whether people accurately estimate, underestimate, or overestimate their actual screen time. Hence, Study 1 of this thesis investigated the accuracy (as compared to iPhone screen time trackers) of digital natives' self-reported screen time estimates. That study also aimed to investigate the influence on objectively measured screen time of (a) individual difference factors (i.e., depression, anxiety, mobile attachment), and (b) environmental context (i.e., day of the week and COVID-19 lockdown restrictions).

The literature reviewed above also suggests the time-emotion paradox might be a viable explanation for why people may not accurately estimate their screen time. The specific notion here is that, because smartphones are usually regarded as affording a sense of pleasure and calm, they may enable a sense of time distortion (i.e., time spent using the device may pass more quickly than time spent being separated from it). Hence, Study 2 of this thesis investigated whether the accuracy of digital natives' subjective estimates of the duration of a waiting situation was influenced by the presence or absence of their smartphone and whether being denied access to the device would induce anxiety.

Chapter Three:
STUDY 1: Smartphone Screen Time: Inaccuracy of self-reports and influence of psychological and contextual factors

This chapter has been published as a peer-reviewed article:

Hodes, L. N. & Thomas, K. G. F. (2021). Smartphone Screen Time: Inaccuracy of self-reports and influence of psychological and contextual factors. *Computers in Human Behavior, 115*. https://doi.org/10.1016/j.chb.2020.106616

The measures used in this study can be found in:

Appendix A: Sociodemographic Questionnaire
Appendix B: Beck Depression Inventory-Second Edition
Appendix C: State-Trait Anxiety Inventory
Appendix D: Mobile Attachment Questionnaire
Appendix E: Instructions for objective screen time report

All ethics-related documents can be found in:

Appendix F: Study 1 advertisements
Appendix G: Study 1 follow-up advertisement
Appendix H: Study 1 consent forms
Appendix I: Study 1 debriefing forms

Abstract

Previous research investigating associations between screen time and various undesirable consequences (e.g., poor mental health) has relied heavily on self-report measures. However, there is debate regarding whether self-reports overestimate or underestimate actual screen time. We used advances in iPhone software to address this question and to investigate the influence of individual difference factors, and COVID-19 lockdown restrictions, on screen time. Participants ($N = 267$, 18–25 years) completed scales measuring depression, anxiety, smartphone attachment, and estimated their screen time. Thereafter, they shared screenshots of their battery use (BUS) and iPhone screen time (iOS STT) data. Some ($n = 24$) shared their BUS data again during the COVID-19 lockdown. Whereas the BUS data (10-day average, including two weekends) indicated that self-reports underestimated actual use, the iOS STT data (7-day average) indicated that self-reports overestimated actual use (ps < .007). Smartphone use was heavier over weekends and screen time increased significantly during the lockdown ($p = .001$). Finally, smartphone attachment mediated the relationship between objective screen time and depression, but not anxiety. We conclude that iPhone tracking features can reliably collect objective screen time data, and that screen time is significantly influenced by both individual difference factors and environmental context.

Highlights:

- iPhone software reliably tracks screen time data
- Self-reported screen time differed significantly from actual screen time
- Screen time was significantly higher over weekends than weekdays
- Screen time increased significantly during the COVID-19 lockdown
- Smartphone attachment mediated the relationship between screen time and depression

Keywords: anxiety; attachment; COVID-19; depression; screen time; smartphones

1. Introduction

Smartphones are among the most ubiquitous and desired objects in contemporary society. Hence, the cyberpsychological literature aims to understand the increasingly prevalent human-smartphone interaction. One key concept and frequently studied outcome in this literature is that of *screen time* (i.e., the amount of time that one spends actively using one's device). Most previously published research on smartphone screen time (or, more generally, on frequency of use) has utilized self-report measures. Many studies have, for instance, tested predictions regarding associations between high levels of self-reported screen time and various undesirable outcomes (e.g., sleep disturbances, depressive symptomatology, obesity, and cognitive problems; see, e.g., Boers et al., 2019; Costigan et al., 2013; Garmy et al., 2018; Montagni et al., 2016).

However, numerous studies comparing subjective and objective measures of various aspects of human behavior suggest that the former is frequently a poor estimate of the latter (see, e.g., Auer & Griffiths, 2017; Chastin et al., 2018). For instance, several studies suggest that individuals typically underestimate the amount of sleep they actually get (see, e.g., Lipinska & Thomas, 2017). Similarly, when reporting to medical professionals, smokers typically underestimate the amount they actually smoke (see, e.g., Ebner et al., 2013; Wolvers et al., 2020). More germane to the current purposes are studies showing that individual self-reports regarding the amount of time spent browsing Facebook and watching television are significant underestimates when compared to objective data derived from computer and television tracking software (Junco, 2013; Otten et al., 2010).

The same data patterns are observed in studies of self-reports regarding mobile device screen time. For instance, Lin and colleagues (2015; $N = 79$, $M_{\text{age}} = 22.4 \pm 2.3$ years) and Felisoni and Godoi (2018; $N = 43$ undergraduates) found that young adults significantly *underestimated* (relative to objective data gathered by a tracking application) the amount of time they spent on their smartphones. Such findings are not universal, however. Kobayashi and Boase (2012) reported that their adult participants ($N = 310$, age range = 20–69 years) significantly *overestimated* (again, relative to objective data gathered by a tracking application) the amount of time they spent on their smartphones. Studies using phone bills as objective measures also report finding subjective overestimates of time spent using cell phones[1] (Boase & Ling, 2013; Shum et al., 2011).

[1]Although the focus of this study is on smartphones, the literature we review includes research conducted on *cell phones* (i.e., handheld devices that only allow calls and simple text messages). *Smartphones* are handheld devices that have all the functionality of a cell phone but that also have powerful computing capabilities (e.g.,

A minor limitation of studies that use tracking applications to gather objective data regarding screen time is that they do not record activity when the smartphone is set in airplane mode. A more significant limitation of those studies, however, is that participants are required to download the application onto their phones (Andrews et al., 2015; Christensen et al., 2016; Rahmati & Zhong, 2012). In some cases (e.g., Felisoni & Godoi, 2018; Kobayashi & Boase, 2012; Lee et al., 2017; Lin et al., 2015; Shaw et al., 2020), this download happens after they have completed baseline measures that have explicitly asked them to estimate their screen time. Hence, it is likely that in such studies participants are aware their screen time is being monitored. This awareness can lead to behavioral change around the outcome variables (i.e., when one knows one's screen time is being tracked, one might change one's behavior to match what one thinks the researcher desires). It is important to avoid this potential Hawthorne effect when designing such studies.

Recent advances in the iPhone operating system (OS) and associated software might help study designs mitigate this threat to internal validity. For instance, a battery use screenshot (BUS) appears to be a reliable and feasible way to collect real-time data regarding screen time, and a built-in screen time tracker (iOS STT) allows users to set personal limits on their use (Ellis et al., 2019; Gower & Moreno, 2018; *Set screen time, allowances, and limits on iPhone*, 2019). Of note here is that screen time as measured by the BUS and iOS STT are not strictly comparable: The former takes an average over the previous 10 days of use, whereas the latter takes an average over the previous 7 days of use. Hence, there is the potential for the former to include two weekends in its estimate while the latter would include only one. Given that weekend days are frequently associated with heavier use (see, e.g., Liu et al., 2019; Yang et al., 2018), this difference in periods of estimation might be important to consider.

1.1 Individual difference factors

Personal and/or sociopolitical context might affect screen time or smartphone use (see, e.g., Shaw et al., 2018). For instance, when an individual is busy with work demands one might expect them to spend less time on their phone than when those demands are relatively light. Often this difference is reflected in weekday versus weekend use. Yang and colleagues (2018) reported that, in a sample of adolescent students ($N = 218$, $M_{\text{age}} = 18.23 \pm 0.91$ years), those who self-identified as heavy smartphone users (i.e., more than 3

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they allow Internet access, can run gaming and productivity applications, and are equipped with a digital camera).

hours use daily) reported higher use on the weekend than on weekdays (but see Wilcockson et al., 2018, for contrasting data). Similarly, people might spend more time following the news on their smartphone under conditions of political or social crisis (e.g., the COVID-19 pandemic).

Several previous studies have investigated associations between affective states and screen time (see, e.g., Boers et al., 2019; Boumosleh & Jaalouk, 2017; Elhai et al., 2016; Lepp et al., 2014). A common finding is that young adults who report high levels of depression or anxiety also report high levels of smartphone screen time (see, e.g., Demirci et al., 2015; Hussain et al., 2017). Of note, however, is that Rozgonjuk and colleagues (2018) found, in a sample of undergraduate students, (a) no significant association between self-reported depression and an objective measure of screen time (a tracking application), and (b) no direct association between self-reported anxiety and that measure of screen time.

A small body of research has focused on another key individual difference factor in smartphone screen time: mobile attachment (see, e.g., Konok et al., 2016; Konok et al., 2017; Meschtscherjakov et al., 2014). Drawing on seminal work in developmental psychology (Ainsworth & Bell, 1970; Bowlby, 1958), cyberpsychologists define this construct as suggesting that individuals have particular levels of emotional attachment to their mobile devices, and specify that it includes components related to feelings of separation insecurity and separation anxiety when the device is not at hand, and of having a safe haven and a secure base when it is (Konok et al., 2016; Meschtscherjakov et al., 2014). Hence, at some levels of mobile attachment separation does not cause distress (signifying a healthy secure attachment), whereas at other levels it does (signifying an unhealthy anxious attachment).

However, few empirical studies have investigated whether the degree of attachment people have to their smartphones might mediate relations between device use/screen time and affective outcomes. We suggest this mediation might be possible because prior research suggests that (a) screen time and anxiety/depression may not always be directly related (see, e.g., Elhai et al., 2017; Panova & Lleras, 2016; Rozgonjuk et al., 2018), (b) screen time and mobile attachment/dependence are associated (Bae, 2017; Konok et al., 2016; Lee et al., 2014), and (c) attachment, in the classical sense, is strongly associated with anxiety/depression (see, e.g., Joeng et al., 2017; Karreman et al., 2018; Scharfe, 2007; Scheffold et al., 2018).

1.2. The current study

We used recent iOS technological advances to address key methodological limitations of previously published studies in this field, and to thereby fill knowledge gaps regarding the differences between actual and estimated smartphone screen time. Using a sample of young adults, we tested this primary hypothesis: (1) objective measures of screen time (i.e., those taken from the iPhone's BUS and iOS STT) will be significantly different from subjective estimates.

Additionally, because we were interested in the influence of individual difference factors on smartphone use, and because the COVID-19 pandemic and associated governmental responses allowed us to examine the influence of environmental contextual factors on smartphone use, we tested these additional hypotheses: (2) participants will report higher use over the weekend than during the week; (3) screen time will increase significantly from levels during a week before the COVID-19 lockdown to levels during a lockdown week; and (4) smartphone attachment will mediate the relationship between screen time and affective outcomes (specifically, depression and anxiety).

2. Methods

2.1 Participants

Using convenience sampling, we recruited 267 undergraduate volunteers (205 women, 62 men) from the diverse student population of a public residential university located in the Western Cape province of South Africa. They were required to be aged between 18 and 25 years and to own an iPhone with the OS 12 update or a more recent version installed. The age criterion limited the sample to digital natives (a term describing people who have grown up with these devices; they are a different population to digital immigrants, which is a term describing people born before the widespread adoption of personal computers and smartphones, and who may have had to learn to adjust to the digital world; Prensky, 2001). There were no other inclusion or exclusion criteria.

Twenty-four of this group of 267 (20 women, 4 men) provided data at two time points: Once several months before the COVID-19 lockdown, and once during the lockdown. We used their baseline and follow-up data to test Hypothesis 3.

An a priori power analysis using G*Power software (Faul et al., 2009) suggested that, in order to generate statistical power ($1 - \beta$) of at least .85 with parameters set at analysis = two-tailed *t*-test, Cohen's $d = 0.20$ (a small effect size), and $\alpha = .05$, one would require a sample size of 227. Hence, at $N = 267$ the study was adequately powered to test the main hypothesis.

2.2 Measures

The self-report questionnaires described below gathered information about sociodemographic characteristics and individual difference factors (current depressive symptoms, trait anxiety, and mobile attachment) that previous research suggests might influence associations between objective and subjective estimates of smartphone use (see, e.g., Demirci et al., 2015; Konok et al., 2016; Panova & Lleras, 2016; Stiglic & Viner, 2019).

A study-specific *sociodemographic questionnaire* gathered information about the participant's age, sex, and highest level of education. The 21-item *Beck Depression Inventory-Second Edition* (*BDI-II;* Beck et al., 1996) is a widely used standardized self-report instrument that gathers information regarding levels of depression over the 2 weeks prior to reporting. Higher BDI-II scores indicate higher levels of depressive symptomatology. The 20-item *State-Trait Anxiety Inventory* (*STAI-Trait;* Spielberger et al., 1983) is the most commonly used self-report measure of trait anxiety (i.e., anxiety as a personality trait that remains stable over time; Spielberger & Vagg, 1984). Higher scores indicate greater levels of trait anxiety. The 15-item *Mobile Attachment Questionnaire* (*MAQ*; Kornok et al., 2017) measured four key aspects of smartphone attachment, including how insecure and/or anxious the respondent feels when separated from the device, and how much the device feels like a safe haven and secure base for them. Higher scores indicate higher levels of attachment.

We measured *subjective screen time* by asking participants to answer the following questions: (1) On average, how long do you think you spend on your smartphone each day? (2) Based on your previous answer, how long do you think you spend on your smartphone in a week?

Regarding our measurement of *objective screen time*, recent versions of the iOS software allow the user to generate detailed reports on (a) their screen time over the previous 7 days (this is our iOS STT variable), and (b) their battery use over the previous 10 days (this is our BUS variable). Each of these reports presents information about the total number of hours and minutes they spent on their phone over that period, as well as the amount of time they spent on each application over that period (see Figure 1). Unlike some other screen time trackers, iOS software records activity whenever the smartphone is switched on (i.e., even when it is in airplane mode). However, the BUS report distinguishes active from passive use (i.e., time spent actively using one's smartphone versus background activity). To facilitate the generation of iOS STT reports, the user must activate the feature. In contrast, BUS tracking is automatic as long as the smartphone is equipped with at least the iOS 8 update.

We asked participants to email us a screenshot of each of these reports. We also invited them to use that email to reflect qualitatively on their screen time reports by "comment[ing] on any outcomes that you were surprised by."

Figure 1. An example of a screen time (left) and a battery use (right) iPhone report. Note that both reports provide information regarding total activity and activity within the most-used applications. The battery use report, however, distinguishes between active use (i.e., active engagement with an application, for instance by typing or by watching stimuli on the screen) and background activity.

2.3 Main study procedure

We emailed a study invitation via undergraduate course websites. A link embedded within the invitation redirected potential participants to an online survey. In the survey, measures were administered as follows: sociodemographic questionnaire, BDI-II, MAQ, STAI-Trait, and self-reported screen time questions. After completing the survey, the participant was asked to take screenshots of their screen time and battery use reports and email them to a study-specific address. Study procedures were granted ethical approval by our institution's research ethics committee.

A unique link to the survey was posted at 08h00 each Monday morning of the data collection period. That link was available until 17h00 the same day. This aimed to ensure that all data received covered the same period of time for all participants. For instance, a survey link sent out on Monday September 16 collected screen time data from September 9–16 (i.e., one full week, including both weekend days), and so on for the remaining data-collection Mondays. Data were collected on three separate Mondays in September and October 2019.

2.4 Follow-up study procedure

In April 2020, we emailed all participants who had completed the main study procedures an invitation to participate in a COVID-19 follow-up study. Their participation simply required them to email a BUS report on either Monday April 20 or Monday April 27 (i.e., during the third or fourth week of COVID-19 lockdown in South Africa). Again, we invited them to use their email report to reflect qualitatively on their screen time reports by "comment[ing] on any outcomes that you were surprised by." Collecting the data on Mondays ensured we would be able to make a fair comparison of their COVID-19 BUS report with their original BUS report.

2.5 Data management and statistical analyses

We used SPSS (version 25.0) to complete all statistical analyses. Following convention, we set α at .05 in making decisions about statistical significance. We scored the questionnaires following standard protocols. Missing demographic data were deleted listwise. If participants provided a range for their self-report screen time estimate, we used the midpoint of that range. Analyses of the consequent data then proceeded across five discrete steps. First, we generated a set of descriptive statistics for data from each of the sociodemographic questionnaire, BDI-II, STAI-Trait, MAQ, and screen time measures to identify outliers, potential trends, and confounders, and to test assumptions underlying parametric statistical tests. We did not exclude or otherwise adjust for outlying data points.

Second, a series of Wilcoxon signed-ranks tests evaluated Hypothesis 1 by assessing the magnitude of differences between subjective and objective screen time measures. We used nonparametric statistical techniques to analyze these data because self-reported and iOS STT screen time data were not normally distributed.

Third, we began evaluation of Hypothesis 2 by extracting, from each participant's BUS graph, the two days on which they had the heaviest use (i.e., the two days on which active use time was highest). Because the BUS data cover 10 consecutive days, we made the decision to extract only unique days. So, for instance, if the graphs indicated that Week 1 Sunday and Week 2 Sunday were the two days of heaviest use, we only included the heaviest of those two and then extracted the next-heaviest day. Two chi-square goodness-of-fit tests then assessed if, for the set of highest and second-highest use days separately, there were significant differences in the frequency with which each day of the week was endorsed.

Fourth, a paired-samples t-test evaluated Hypothesis 3 by assessing the magnitude of differences between BUS-measured screen time at pre-lockdown versus during lockdown. Here we used only BUS-measured screen time because (a) we did not ask for the subjective estimate at the second time of measurement, and (b) minor software changes in the iOS STT measure between the two measurement timepoints meant the pre-lockdown and lockdown data would not have been comparable.

Finally, we evaluated Hypothesis 4 by using (a) a series of bivariate correlational analyses to assess magnitude of associations between individual difference factors (i.e., depression, trait anxiety, and smartphone attachment) and BUS-measured screen time (because this measure provided the most complete and normally distributed screen time data set), and (b) a series of regression models (see Figure 2) and follow-up Sobel (1982) tests.

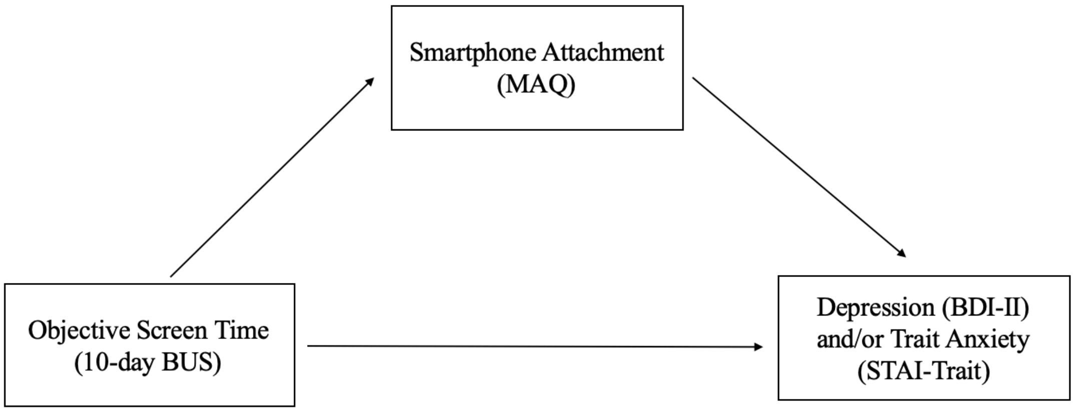


Figure 2. The hypothesized mediating role of smartphone attachment in the relationship between screen time and depression and/or trait anxiety.

3. Results

3.1 Descriptive data

Table 1 summarizes the sample's sociodemographic and other characteristics. Regarding depressive symptomatology, most participants (n = 186; 69.70%) scored ≤19 on the BDI-II, indicating reports of no more than what is conventionally described as "mild depression" (Beck et al., 1996). Only 29 participants (10.86%) scored in the range conventionally described as "severe depression" (i.e., scores ≥29). Regarding trait anxiety, a one-sample t-test suggested that, on average, the current participants scored significantly higher on the STAI-Trait (i.e., were significantly more anxiety-prone) than college students in the standardization sample, $t(271) = 14.34$, $p < .001$ (Spielberger et al., 1983). Regarding mobile attachment, no previously published study has reported on norms for the MAQ. However, the MAQ mean and standard deviation in this sample were strikingly similar to those reported by Hodes and colleagues (2020), who also collected data from undergraduate students aged 18–25 years. In both cases, the sample's average score suggested quite strong mobile attachment.

Regarding the screen time measures, all three had similar minimum values. However, the maximum value for self-reported screen time was much higher than that for the two objective measures. Additionally, the standard deviation for self-reported screen time was relatively large, indicating substantially more variability in the subjective than in the objective estimates. Further analyses on the distribution of self-reported screen time revealed that it was severely skewed to the right (skewness = 1.86 ± 0.15; kurtosis = 4.10 ± 0.30). The distribution of 7-day iOS STT scores was also skewed to the right (skewness = 0.98 ± 0.16; kurtosis = 1.31 ± 0.33), albeit not as severely. However, the distribution of 10-day BUS scores was normally distributed (skewness = 0.62 ± 0.16; kurtosis = 0.25 ± 0.31).

Table 1.
Sample Sociodemographic Characteristics and Screen Time Estimates: Descriptive data (N = 267)

			95% CI[a]	
Variable	*M* (*SD*)	Range	LL	UL
Age (years)	20.48 (1.51)	18–25	20.31	20.67
BDI-II	15.62 (9.50)	0–45	14.52	16.76
STAI-Trait	47.98 (11.03)	22–75	46.65	49.33
MAQ	48.61 (12.53)	18–75	47.14	50.19
Screen Time (mins / day)				
Self-reported	331.46 (199.92)	60–1200	306.37	356.73
10-day BUS[b]	344.47 (135.18)	61–773	122.01	147.20
7-day iOS STT[c]	321.60 (134.35)	68–851	303.55	340.39

Note. BDI-II = Beck Depression Inventory-Second Edition; STAI = State-Trait Anxiety Inventory; MAQ = Mobile Attachment Questionnaire; BUS = battery use screenshot; iOS STT = iPhone operating system screen time tracker; CI = confidence interval; LL = lower limit; UL = upper limit.
[a]95% confidence intervals bootstrapped by 1000 iterations
[b]Based on *n* = 244 because 23 participants sent their data over an incorrect timeframe (i.e., they sent a 1-day rather than 10-day average).
[c]Based on *n* = 219 because 48 participants either did not have this feature active or sent the incorrect data (i.e., they sent a 1-day rather than 7-day average).

3.2 Hypothesis 1: Objective measures of screen time (i.e., those taken from the iPhone's BUS and iOS STT) will be significantly different from subjective estimates

Subjective and objective estimates of screen time were, on the face of it, quite similar (see Table 1). Bivariate correlational analyses confirmed this impression, finding that each bore a significant relation to the others, all *p*s < .001. There were no significant sex differences on all three measures, *ps* > .10.

For the comparison between self-reported screen time and screen time as measured by the 10-day BUS average, analyses indicated that participants significantly underestimated the amount of time they actually spent on their smartphones, $Z = -3.529$, $p < .001$, Cohen's $d = 0.001$. For the comparison between self-reported screen time and screen time as measured by 7-day iOS STT average, analyses indicated that participants significantly overestimated the amount of time they actually spent on their smartphones, $Z = -2.579$, $p = .010$, Cohen's $d = 0.05$. Finally, analyses detected a significant difference between the two objective measures of screen time, $Z = -5.922$, $p < .001$, Cohen's $d = 0.17$.

3.3 Hypothesis 2: Participants will report more smartphone use over the weekend than during the week

Participants appeared to use their smartphones more heavily on Sunday than on any other day (see Figure 3 and Figure 4). Regarding both day of heaviest use and day of second-heaviest use, analyses detected a statistically significant discrepancy in frequency of endorsed day, $\chi^2(6, N = 240) = 51.32$, $p < .001$, Cramer's $V = 0.005$, and $\chi^2(6, N = 240) = 11.78$, $p = .002$, Cramer's $V = 0.004$, respectively.

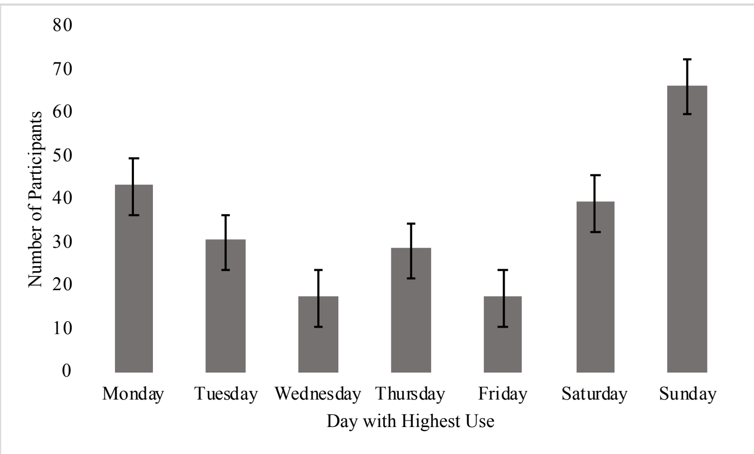


Figure 3. Frequencies of the days with highest smartphone use (based on 10-day BUS report; $N = 240$). Confidence intervals are standard error of the mean.

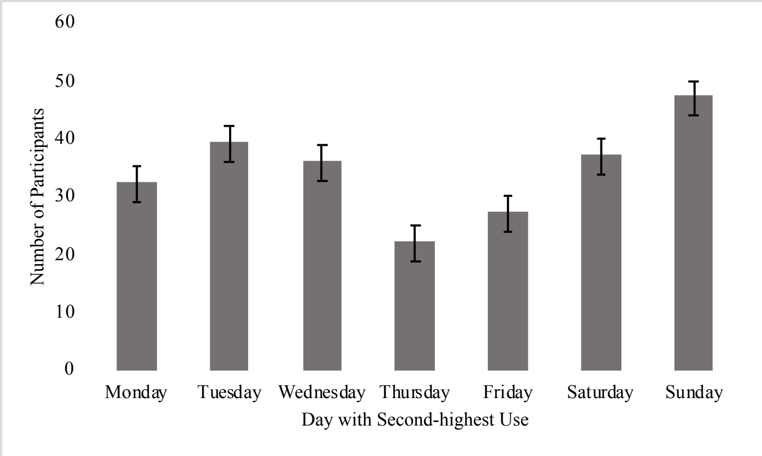


Figure 4. Frequencies of the days with the second-highest smartphone use (based on 10-day BUS report; $N = 240$). Confidence intervals are standard error of the mean.

3.4 Hypothesis 3: Screen time levels will increase significantly from measurement taken during a week before the COVID-19 lockdown to measurement taken during a lockdown week

We analyzed data from the 24 participants who provided pre-lockdown (M = 269.54±97.42 mins / day) and lockdown (M = 348.46±156.85 mins / day) data. The analysis detected a statistically significant difference, $t(23) = -3.86$, $p = .001$, Cohen's $d = 0.60$.

3.5 Hypothesis 4: Smartphone attachment will mediate the relationship between screen time and affective outcomes (specifically, depression and anxiety)

The analyses presented in Table 2 indicated that BUS-measured screen time was significantly positively associated with depressive symptomatology, $p = .033$, and with degree of smartphone attachment, $p \leq .001$. There was no significant association between BUS-measured screen time and trait anxiety, $p = .129$. Degree of smartphone attachment was significantly positively associated with both depressive symptomatology and trait anxiety, ps $\leq .001$.

Table 2.
Correlation Matrix: Associations between measures of screen time, depression, anxiety, and smartphone attachment (N = 267)

	1	2	3
1. 10-day BUS[a]	1.00		
2. BDI-II	.137*	1.00	
3. STAI-Trait	.097	.799***	1.00
4. MAQ	.323***	.235***	.341***

Note. Values reported are Pearson's *r* correlation coefficient. All correlations were positive (i.e., signs are excluded as none of the correlations were negative). BUS = battery use screenshot, 10-day average; BDI-II = Beck Depression Inventory-Second Edition; STAI-Trait = State-Trait Anxiety Inventory; MAQ = Mobile Attachment Questionnaire.
[a]Based on $n = 244$ because 23 participants sent their data over an incorrect timeframe (i.e., they sent a 1-day rather than 10-day average).
*$p < .05$. **$p < .01$. ***$p < .001$. All *p*-values are two-tailed.

Because there was no significant correlation between BUS and STAI-Trait scores, we reasoned that smartphone attachment could not mediate the relationship between screen time and trait anxiety, and did not pursue any further analyses in this regard.

To investigate the possible mediating effect of smartphone attachment on the relationship between screen time and depressive symptomatology, we regressed (1) BUS-measured screen time on BDI-II scores, (2) BUS-measured screen time on MAQ scores, and (3) both BUS-measured screen time and MAQ scores on BDI-II scores. As Figure 5 shows, smartphone attachment mediated the relationship between objectively measured screen time and depressive symptomatology, Sobel's $z = 2.92$, $p < .001$. In this instance, there is complete mediation as the indirect effect is not statistically significant.

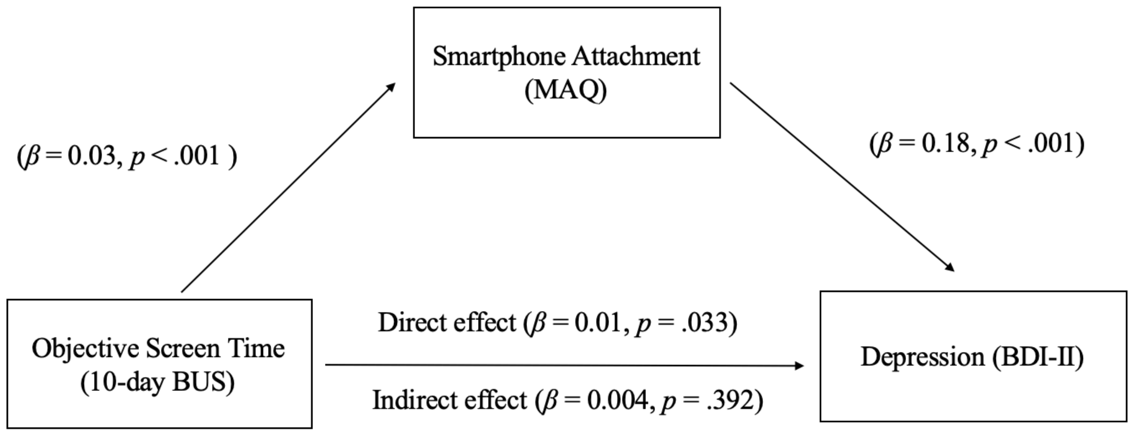


Figure 5. Mediating role of smartphone attachment on the relationship between screen time and depression. BUS = Battery Use Screenshot; MAQ = Mobile Attachment Questionnaire; BDI-II = Beck Depression Inventory-Second Edition. For the direct effect of screen time on smartphone attachment, 95% CI (.019-.041), *SE* = 0.006. For the direct effect of smartphone attachment on depression, 95% CI (.09-.27), *SE* = 0.05. For the direct effect of screen time on depression, 95% CI (0.001-0.02), *SE* = 0.004. For the indirect effect of screen time on depression, 95% CI (-.005-.013), *SE* = .005. All beta values are unstandardized.

4. Discussion

This study's primary objective was to examine the accuracy, or inaccuracy, of self-reported screen time in a sample of undergraduate students who were digital natives (i.e., individuals who have grown up with smartphones; Prensky, 2001). To accomplish this objective, we investigated the difference between subjective screen time (i.e., an individual's estimation of how much they use their smartphone each day) and two objective measures of screen time (i.e., those taken from the iPhone's battery use screenshot [BUS] and built-in screen-time tracker [iOS STT]). Our descriptive analyses suggested that, although self-report measures of screen time appear, on average, to be comparable to objective measures, the latter have the advantage of more precise daily usage estimates and reduce the possibility of grossly outlying values. Our inferential analyses confirmed the a priori hypothesis that objective and subjective measures of screen time will be significantly different from one another. This finding is consistent with previously published research suggesting that self-report smartphone use scales are inaccurate measures of actual smartphone screen time (see, e.g., Andrews et al., 2015; Ellis et al., 2019).

Compared to the iOS STT data (reported as an average over 7 days), participants significantly *overestimated* the amount of time they spent on their smartphones each day. The direction of this finding is consistent with that reported in a few previous studies (see, e.g., Boase & Ling, 2013; Shum et al., 2011). There are at least two possible explanations for this pattern of data. First, individuals who are more socially engaged (e.g., who have more in-person conversations, and who are party to more phone-based group conversations) tend to overestimate how long they spend interacting on their smartphones (Kobayashi & Boase, 2012). Second, as digital natives are so accustomed to the device's pervasive presence they may overestimate how long they actually use the device because they cannot imagine functioning without it (Ahn & Jung, 2014).

In contrast, compared to the BUS tracker data (reported as an average over 10 days, including two full weekends), participants significantly *underestimated* the amount of time they spent on their smartphones each day. The direction of this finding is consistent with a small body of literature indicating that digital natives significantly underreport the amount of time they spend on their devices (Felisoni & Godoi, 2018; Lin et al., 2015). A common explanation for such patterns of data is that smartphone use has become so habitual that individuals lose track of time when they are engaged with their devices (Fullwood et al., 2017; Shaw et al., 2018).

These apparently contradictory findings, suggesting that participants both overestimated and underestimated their daily smartphone use, may be understood as an artifact of the different time periods over which the objective measures were taken. Key to this difference is that the iOS STT average included one weekend whereas the BUS average included two, and that there was a significant difference between those two objective estimates. As one of our secondary analyses showed, participants tended to use their smartphones more heavily on weekend days (and especially on Sundays) than weekdays. This finding is consistent with previous studies suggesting that students' screen time increases over the weekend, when they usually have no classes and more free time (Liu & Li, 2019; Yang et al., 2018; but see Wilcockson et al., 2018). In other words, it appears that screen time tends to fluctuate quite substantially across the week, with occupational and other demands influencing these fluctuations. Hence, one interpretation of our results is that participants might tend to overestimate the amount of time they spend using their smartphones on weekdays but might underestimate the weekend amount. Future research in this field should consider both the relative inaccuracy of subjective estimates and the fact that asking participants to estimate their use on an 'average' day ignores inevitable (and significant) variability in their schedules.

Another of our secondary analyses explored the repercussions, for screen time, of an externally imposed and society-wide influence on daily schedules: the COVID-19 lockdown. Although this question was not part of our original research plan, we suspected that broad-based changes in the external environment could have profound impacts on screen time. This suspicion arose from observations we made during our primary phase of data collection. For instance, one student reported that "My screen time has gone up these past couple of weeks since Nene's disappearance and subsequent passing[2]. I [have] found myself on my Twitter often to see if there are any reports or warnings about staying away from certain areas." Hence, governmental response to the COVID-19 pandemic provided an ideal opportunity to explore how screen time fluctuates in response to drastic changes in sociopolitical context. Analyses confirmed the a priori hypothesis that screen time (as measured by BUS data) will increase significantly during a lockdown period compared to a similar pre-lockdown period.

Of interest here were participants' qualitative responses that accompanied their lockdown BUS reports. In response to a question asking them to explain why the lockdown may have led them to change their patterns of smartphone use, many reports were consistent with that of a student who said that she found herself engaging with "time-wasting applications, like Candy Crush and TikTok that [she] had not had downloaded prior to the lockdown." A common feeling was captured by one participant who said that their screen time had increased "due to the quarantine and having little motivation to do things some days besides laying in [their] bed on [their] phone." These findings emphasize that smartphones are more than simply devices of communication, but rather are recreational and "friend-like," and are used to alleviate boredom (Fullwood et al., 2017, p. 350).

The notion that people might have emotional relationships with their smartphones is further underscored by findings from another of our secondary analyses. Consistent with previous studies in this literature (Hodes et al., 2020; Prensky, 2001), the current sample of

[2]Quote extracted directly from the participant's email communication with the research team. Uyinene ('Nene') Mrwetyana was a South African student who was kidnapped and murdered in August 2019.

digital natives reported relatively high mobile attachment scores. Qualitatively, they stated that they use their smartphone “as a security blanket in uncomfortable situations” and “to play games when [they are] anxious.”

Also consistent with previous research (Bae, 2017; Konok et al., 2016; Lee et al., 2014), scores on the measure of smartphone attachment were significantly positively correlated with objectively measured screen time. This finding suggests that an individual’s amount of smartphone use is, at least partially, dependent on their emotional attachment to the device. A recent report by Hodes et al. (2020), however, suggests that smartphone use is not necessarily synonymous with attachment. Using the same instruments as Konok et al. (2016), Hodes et al. found that young adults (aged 18–25 years) self-reported lower use but higher attachment whereas older adults (aged 30–60 years) self-reported higher use but lower attachment. Although it seems intuitive that the personal dependence and reliance an individual has on their smartphone should influence the amount of time they estimate spending on the device, it seems possible that one can present with high levels of use (e.g., due to work demands) but low levels of attachment (i.e., because being without the device does not cause anxiety).

Finally, we found that smartphone attachment completely mediated the relationship between screen time and depression. This result suggests that the amount of use itself may not be directly associated with poor mental health (at least in terms of affective status), and is therefore consistent with previous research reporting that objectively measured smartphone screen time is not associated with the severity of depression and anxiety (Rozgonjuk et al., 2018; see also Shaw et al., 2020, for a comparsion between subjective and objective data). Although this mediational finding is novel in the cyberpsychological literature, it again emphasizes the central role that emotional attachment to the device plays in behavioral outcomes and is consistent with many developmental psychology studies in describing a strong relationship between attachment and depression (see, e.g., Scharfe, 2007; Scheffold et al., 2018).

We did not pursue mediational analyses with regard to screen time, smartphone attachment, and anxiety because BUS and STAI-Trait scores were not significantly correlated with one another. Previous studies (e.g., Boumosleh & Jaalouk, 2017; Elhai et al., 2016) have suggested that screen time is significantly positively associated with anxiety. The fact that our analyses did not detect such a relationship may be because the STAI-Trait is not a clinical measure of anxiety-related symptomatology (it measures a general dispositional tendency toward anxious feelings).

There is, of course, some debate in the literature regarding the association between smartphone use and mental health, with several studies finding that affective outcomes are associated with increased self-reported screen time, in some cases even after controlling for numerous other variables (e.g., socioeconomic status, involvement in sporting and/or religious activities; see, e.g., Demirci et al., 2015; Elhai et al., 2016; Twenge et al., 2018). However, in this study as in many previously published investigations, measures of mobile device screen time have focused broadly on *duration* or *frequency* of use rather than on *type* of use. This distinction is likely to be crucial. For instance, Boers et al. (2019) reported that, in a large sample of adolescents (N = 3826), social media use but not gaming was associated with an increase in depression over a 4-year timespan. Hence, future studies in this field should prioritize measurement of the diversity of activities in which individuals engage on their smartphones and the concomitant psychological effects associated with variability in each.

4.1 Limitations and directions for future research

Inferences from this study's findings must be drawn cautiously and after careful consideration of the following limitations. First, we only received follow-up (lockdown) screen time data from a small sub-sample (n = 24) of the original group of participants. Despite several attempts at increasing this sample size, we were unsuccessful in collecting more data. Nonetheless, our between-group comparison was associated with a medium-sized effect (Cohen's d = 0.60), which at the very least suggests that investigation of such questions ought to be pursued in future, larger-scale, research studies. Second, we were only able to assess the influence of a single external factor (i.e., a global public health and sociopolitical crisis) on screen time. It would be worthwhile for future research to assess the influence of more person-level variables (e.g., interpersonal conflict, dual-earner versus single-earner families) on screen time and on mobile attachment. Third, although the iOS STT and BUS reports can both give a breakdown of screen time per specific application, we did not request that level of detail from the screenshots participants sent to us. Hence, we were unable to investigate associations between depression / anxiety and the use of specific types of applications. Finally, our sample was restricted to digital natives and to iPhone users who had installed a particular software update. This eligibility criterion limited the demographic and socioeconomic diversity of the sample, and hence these findings may not be generalizable to, for instance, the population of digital immigrants. Future developments in other operating systems and more widespread distribution of similar pieces of software may allow for larger-scale validation of these findings.

4.2 Conclusions

This study adds to the body of cyberpsychological literature investigating human-smartphone interactions by exposing the shortcomings of self-report screen time measures. Furthermore, it adds a relatively novel element to that literature by demonstrating the effects of sociopolitical events and/or personal demands on smartphone use, and by describing relationships between smartphone use, mobile attachment, and psychological symptomatology. In particular, the results suggest that future research on mobile device screen time should feature reliable and objective measures and should, either by design or by statistical analysis, account for the influence of external factors (i.e., day of week, environmental context, sociopolitical circumstances). Finally, our results suggest that it is useful to consider ways in which attachment to the device might mediate relations between screen time (in its broadest conception) and psychological outcomes. This finding reinforces the need to shift from simply correlating high levels of use with undesirable consequences when attempting to understand the ramifications of increasingly pervasive human-smartphone interactions.

Chapter Four:
STUDY 2: Smartphones and Time Distortion:
Does presence of mobile devices influence time perception?

This chapter has been submitted to, and is under review at a peer-reviewed journal:

Hodes, L. N. & Thomas, K. G. F. (under review). Smartphones and Time Distortion: Does presence of mobile devices influence time perception?. *Computers in Human Behavior Reports.*

The measures used in this study can be found in:

Appendix A: Sociodemographic questionnaire

Appendix B: Beck Depression Inventory- Second Edition

Appendix C: State-Trait Anxiety Inventory

Appendix D: Mobile Attachment Questionnaire

Appendix L: NEO Five-Factor Inventory Revised

All ethics-related documents can be found in:

Appendix M: Study 2 advertisement

Appendix N: Study 2 consent form

Appendix O: Consent to use video footage

Appendix P: Study 2 debriefing form

Abstract

The *time-emotion paradox* proposes that emotional conditions affect time perception. Because, subjectively, smartphones are pleasure-providing and anxiety-alleviating devices, previous cyberpsychological research suggests they might facilitate time distortion. This prediction has not been evaluated experimentally, however. To test whether time spent using a smartphone will feel shorter while time without it will feel longer, we assigned participants (N=55; 18–25 years) to either a Smartphone Present or a Smartphone Absent condition and then had them wait alone while being video recorded and having their heart rate monitored. After 13.5 minutes, they estimated the waiting period's duration. As predicted, all Smartphone Present participants used their devices during the waiting period and significantly underestimated its duration, p<.001, Cohen's d=-1.11. Unexpectedly, Smartphone Absent participants also underestimated the waiting period's duration, p<.001, d=-2.92, and were no more anxious than Smartphone Present participants, ps>.550. Behavioral patterns showed significant between-group differences, however: Smartphone Absent participants showed more signs of both boredom and productivity, ps<.042, $\eta^2 s$ > .08. Hence, it appears they found engaging ways to occupy themselves, thus facilitating their time underestimations. We conclude that smartphone use was pleasant enough to distort time perception, but smartphone absence was not so aversive as to distort it in the opposite direction.

Highlights

- Individuals both with and without access to their smartphones underestimated the duration of a 13.5-min waiting period
- Both Smartphone Absent and Smartphone Present participants showed no significant changes in anxiety over the waiting period
- Participants in the Smartphone Absent group showed significantly more behavioral markers of boredom and productivity

Keywords: anxiety; boredom; smartphone; time perception.

1. Introduction

Human-smartphone interactions are almost omnipresent. Cyberpsychology research attempts to understand what drives these interactions and whether classic theories of human behavior can explain and predict their characteristics. One strand of this research investigates whether time becomes distorted for individuals while they are using their smartphones. For instance, Lin et al. (2015) proposed that heavy users, especially, might find they have spent hours engaged with their smartphones while feeling that only minutes have passed. Such experiences of time distortion might explain research finding discrepancies between subjective estimates and objective measures of screen time (Hodes & Thomas, 2021; Parry et al., 2020).

More generally, experiences of time distortion can be influenced by affective states. The “time-emotion paradox” (Droit-Volet & Gil, 2009, p. 1943) suggests that an individual’s emotional condition affects how time is perceived (i.e., experiencing negative emotions makes the passage of time feel longer, whereas experiencing positive emotions makes it feel shorter). Empirical data supporting this proposal emerge from studies showing that, for instance, time spent exposed to unpleasant music is perceived to be longer than time spent being exposed to pleasant music, even though the periods are of objectively equal duration (Droit-Volet et al., 2013; Noulhiane et al., 2007). In another illustration of how individuals overestimate the time spent experiencing distressing, stressful, or anxiety-provoking situations, Rankin et al. (2019) reported the results of two independent studies assessing time perception of university students while they were awaiting exam results. In both studies, analyses detected significant associations between psychological distress and time perception (i.e., participants who were more distressed indicated that time appeared to be moving more slowly; see also Hancock & Weaver, 2005; Liu & Li, 2019).

Neuroscientific evidence suggests there is a neural basis for the time-emotion paradox. Recent research suggests that time perception is influenced by neuron fatigue; that is to say, the subjective experience of time is changed (it appears to pass more slowly) when, at the cellular level, fatigue has set in (Hayashi & Ivry, 2020). Similarly, Ogden et al. (2019) reported that participants whose sympathetic nervous systems (SNS) were activated under conditions of high arousal experienced time distortion (again, they perceived time to be passing more slowly than it actually was). This link between SNS activation and time perception reaffirms the possibility of emotionally-distorted time.

Of particular relevance to cyberpsychology, and to the current investigation, is the finding by Rau et al. (2006) that both novice and professional online gamers overestimated the duration of a forced break that happened after 30 minutes of gaming. These gamers considered that break interval as aversive because they were restrained from playing (i.e., they had been removed from a pleasant experience).

For many people, using a smartphone is a similarly pleasant and immersive experience. Across several research studies, participants report that these devices provide a form of recreation and a sense of confidence, and that they alleviate boredom (Fullwood et al., 2017; Jung, 2014; Leung, 2020). Hence, applied here predictions derived from the time-emotion paradox theoretical framework might state that people will subjectively underestimate the amount of time they spend using their smartphones.

The same theoretical framework would support a prediction stating that people will subjectively overestimate the amount of time they spend without their smartphones. This is because smartphones can alleviate stress and thereby provide a "security blanket" (Panova & Lleras, 2016, p. 253). In behavioral studies supporting this assertion, a researcher takes away the participant's smartphone under a study-related pretext and then assesses the individual's consequent reactions. Using such manipulations, researchers have shown that smartphone separation results in increased subjective anxiety and in significant increases in heart rate and galvanic skin response (see, e.g., Cheever et al., 2014; Clayton et al., 2015). If people experience such psychological distress when their smartphones are removed from their possession, then it is reasonable to hypothesize that their time perception might be distorted during the period of separation (specifically, that they would overestimate the duration of that period).

Researchers using smartphone-separation paradigms have also reported that participants seek proximity toward where their smartphone is stored (Konok et al., 2017). The roots of this seeking behavior are likely in the attachment they have to their smartphones. Just as the classical psychological theory suggests that infants have emotional attachments (either secure or anxious) to their primary caregiver (Bowlby, 1958), the cyberpsychological literature suggests that individuals form emotional attachments to their smartphones. Specifically, mobile attachment entails feelings of separation insecurity and separation anxiety when the device is not at hand, and of having a safe haven and a secure base when it is (Konok et al., 2016; Meschtscherjakov et al., 2014). Hence, it is also reasonable to hypothesize that, under conditions of smartphone separation, participants will seek proximity towards their device.

In contrast, under conditions of smartphone presence the typically observed behavior is that people use their devices, even if they are not alone (Brown et al., 2016). Both Ward et al. (2017) and Froese et al. (2012) reported that in their young adult samples (N = 548, M_{age} = 21.2±2.4 years; N = 693, M_{age} = 20.5 years, respectively) the mere presence of a smartphone was distracting (e.g., individuals divided their attention during tasks to check their device). On the other hand, young adults report that their smartphones provide a form of recreation, alleviate boredom, and reduce anxiety during potentially stressful situations (see, e.g., Fullwood et al., 2017; Panova & Lleras, 2016). Hence, it appears reasonable to hypothesize that when an individual's smartphone is present they will be less productive, but will also be less bored, than if the device was not in their possession.

1.1. The Current Study. Although the literature reviewed above suggests that a fruitful avenue of scientific exploration might involve assessing whether time distortion is at least partly responsible for poor subjective estimations of screen time, no published study has tested this hypothesis experimentally. This study, which was of a cross-sectional between-subjects true experimental design, aimed to conduct such a test: We assessed differences in time perception under smartphone-present and smartphone-absent conditions (i.e., we asked healthy young adults to estimate the duration of a waiting period spent with and without their smartphone). We tested the following hypotheses:

1. Participants assigned to the Smartphone Present condition will (a) subjectively underestimate the duration of the waiting period, (b) not report increased anxiety from baseline through the end of the waiting period, and (c) use their devices heavily during the waiting period.
2. Participants assigned to the Smartphone Absent condition will (a) subjectively overestimate the duration of the waiting period, (b) report increased anxiety from baseline through the end of the waiting period, and (c) spend at least some time seeking proximity towards their device (e.g., will walk toward the location where they know their device is stored).
3. During the waiting period, participants assigned to the Smartphone Absent condition will, relative to those in the Smartphone Present condition, (a) show more behaviors consistent with increased boredom (e.g., look around the room), and (b) engage in more productive behaviors (e.g., read a book).

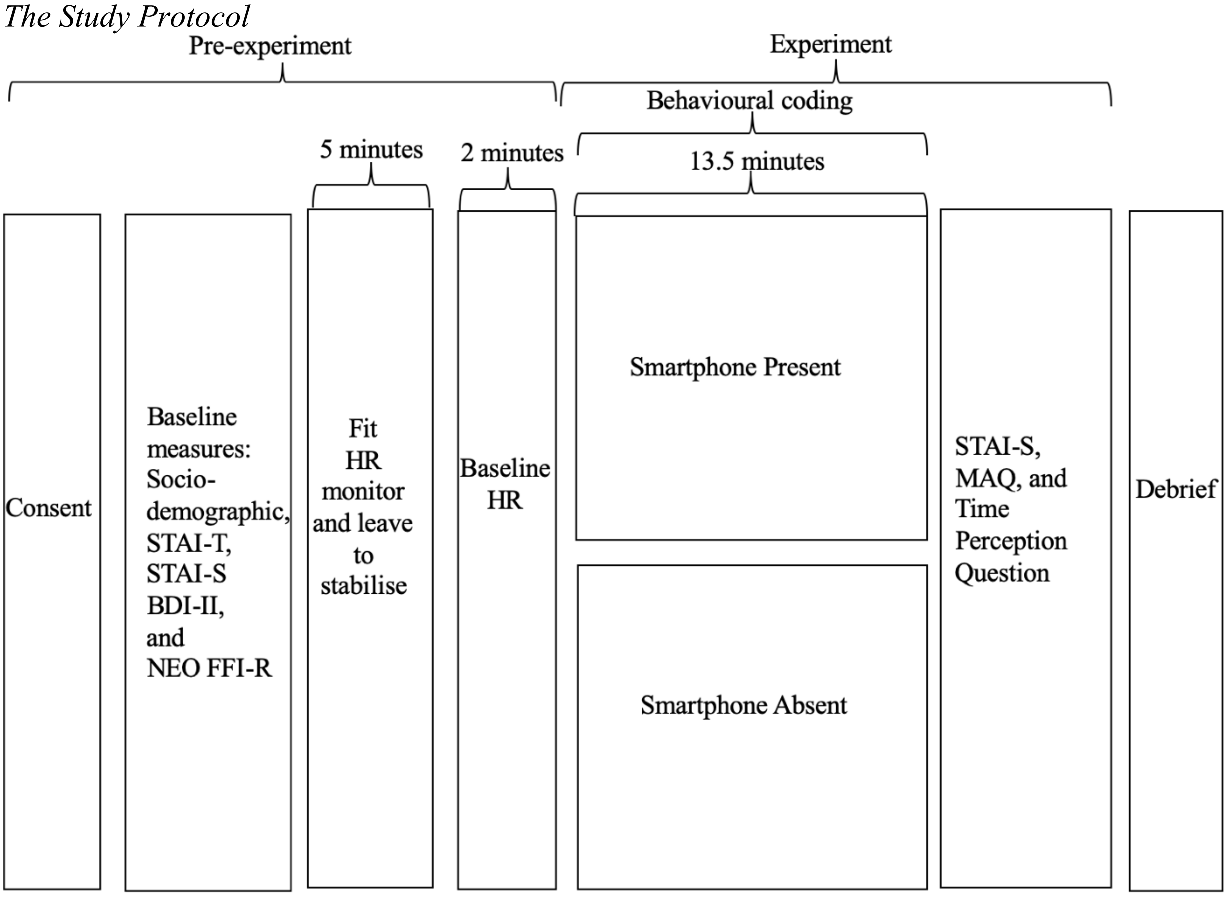
2. Method

2.1. Participants. We used convenience sampling to recruit 55 undergraduate volunteers (44 women, 11 men). Participants were required to be between the ages of 18 and 25 years and to have no history of any serious medical or psychiatric disorder. The age criterion limited the sample to digital natives (i.e., people who grew up with smartphones), who are more likely than digital immigrants (i.e., people born before the widespread adoption of personal computers and smartphones, and who may have had to learn to adjust to the digital world) to have a strong attachment to their devices (Hodes et al., 2020; Prensky, 2001). There were no other inclusion or exclusion criteria.

The study protocol received ethical approval from our institutional ethics committee and was conducted following the Declaration of Helsinki (World Medical World Medical Association, 2013) guidelines. Participants received course credit in exchange for their involvement.

2.2. Materials and Procedure. Figure 1 outlines the entire study protocol.

Figure 1
The Study Protocol

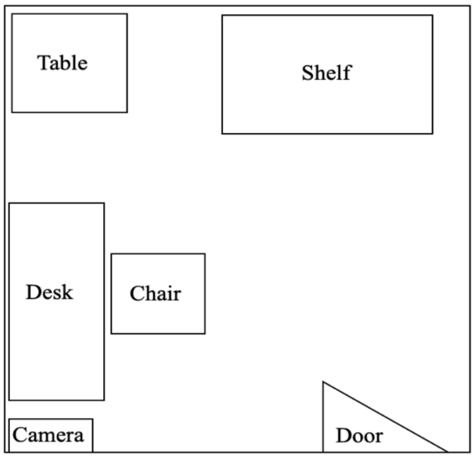


Note. STAI-T = State-Trait Anxiety Inventory-Trait form; STAI-S = State-Trait Anxiety Inventory-State form; BDI-II = Beck Depression Inventory-Second Edition; NEO-FFI-R = NEO Five Factor Inventory-Revised; HR = heart rate; MAQ = Mobile Attachment Questionnaire.

2.2.1. Pre-experimental procedure. We invited participation using an advertisement placed on a course-specific electronic bulletin board. Students were told they could sign up for a mood and personality study that would require them to complete a computer task. A link within the advertisement redirected interested individuals to a scheduling application that would allow them to book a participation time slot.

At the appointed time, a researcher (LH) welcomed the participant into our laboratory and guided them to the study room. This room measured 2.4 x 2.9 m and contained an empty desk, a chair, a table, pictures on the walls, a ceiling-mounted video camera, and an empty shelf (see Figure 2). The participant was seated at the desk.

Figure 2
Schematic of the Study Room



Once seated, the participant read and signed informed consent documents and then completed (in this order, and on an iPad with the time concealed) a sociodemographic questionnaire, the Beck Depression Inventory-Second Edition (BDI-II; Beck et al., 1996), the NEO Five-Factor Inventory Revised (NEO-FFI-R; Costa & McCrae, 1992), and the State-Trait Anxiety Inventory (STAI; Spielberger et al., 1983).

The study-specific *sociodemographic questionnaire* gathered information about the participant's age, sex, and highest level of education. The 21-item *BDI-II* is a widely used standardized self-report instrument that gathers information regarding levels of depressive symptomatology over the 2 weeks prior to reporting. Higher BDI-II scores indicate higher levels of symptomatology. The 60-item *NEO-FFI-R* assesses an individual's balance of the Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism). We administered only the 24 items assessing *extraversion versus introversion* and *neuroticism versus emotional stability* because previous research has suggested that these traits influence smartphone attachment (see, e.g., Hussain et al., 2017; Meschtscherjakov et al., 2014). Each of these items is scored on a 5-point Likert-type scale, with response options ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Negatively worded items are reverse scored to help reduce response sets. Higher overall scores indicate a greater tendency toward displaying the personality trait in question. The *STAI* comprises two 20-item components: Form Y1 (the State form) measures an individual's current level of anxiety, while Form Y2 (the Trait form) measures an individual's general level of anxiety. Each item is rated using a 4-point Likert-type scale, indicating how applicable the given statement is to the respondent. Negatively worded items are reverse scored to help reduce response sets. Higher *STAI-State* scores indicate higher levels of current anxiety; higher *STAI-Trait* scores indicate greater trait anxiety (Julian, 2011).

After the participant completed those questionnaires, the researcher fitted them with a heart rate (HR) monitor (Polar Electro h10 Heart Rate Sensor; Kempele, Finland). This non-invasive and portable device monitored physiological changes that could indicate increasing anxiety (viz., increased HR) continuously throughout the experimental session. Immediately after fitting the device, the researcher waited for the device to normalize to the participant's HR. After normalization, the researcher took average HR measurements from each of the following periods: (a) a 1-min baseline immediately following the stabilization period (HR_1), and (b) the 13.5-min period encompassing the experimental manipulation (HR_2).

2.2.2. Experimental manipulation. We used an online application (www.randomizer.com) to randomly assign participants to either the Smartphone Present (n = 31) or Smartphone Absent (n = 24) condition. Unequal sample sizes were a product of the randomization process.

2.2.2.1 Smartphone Present condition. The researcher informed the participant that because another participant was still busy completing the computer task (this was a deceptive piece of information; there was no other participant), they would have to wait in the study room with the HR monitor attached. The researcher then left the room, ostensibly to check on the other participant. However, before leaving she primed the participant to use their smartphone by saying, "You can use your phone while you wait" or "It's OK to use your phone while you wait."

The participant was then left alone in the study room for 13.5 minutes. The duration of the waiting period was motivated by the following reasons: (1) we required it to be a reasonably unexpected number (e.g., not a multiple of 5 or 10) so that guessing it would be relatively difficult, and (2) individuals tend to have more cognitive availability for even numbers (Hines, 1990). In waiting situations such as this, it is common for people to use their smartphones (see, e.g., Brown et al., 2016). After 12.5 minutes had elapsed, the experimenter opened and shut the door to an adjacent room and said, loud enough for the participant to hear, "Thank you so much for coming." This act aimed to alert the participant to the fact that their waiting time was almost at an end. Precisely 1 minute later, the researcher re-entered the study room carrying a laptop, thus extending the deception that a computer task was central to the study protocol. She asked the participant to complete (again, on an iPad with the time concealed) the STAI-State, the *Mobile Attachment Questionnaire* (MAQ; Kornok et al., 2017), and a study-specific *time perception question*. The 15-item MAQ measures four key aspects of smartphone attachment, including how insecure and/or anxious the respondent feels when separated from the device, and how much the device feels like a safe haven and secure base for them. Higher scores indicate higher levels of attachment. The time perception question ("If you had to estimate, how long did you wait for the researcher to return to the room?") assessed the participant's perception of the waiting period's duration.

2.2.2.2 Smartphone Absent condition. Procedures were identical to those of the Smartphone Present condition, with this exception: Before leaving the study room, the researcher asked for the participant's smartphone (and watch, if they had one), under the pretext that these devices would interfere with the HR monitor's recordings. The participants' device(s) were placed in a box on the table in the study room.

In both conditions, we video recorded the participant's behavior in the waiting situation. Recording started when the researcher left the study room and ended when she re-entered.

2.3. Data Management and Statistical Analyses. We completed all analyses using R Studio Package and SPSS (version 26.0), with the threshold for statistical significance set at $p = .05$ unless noted otherwise below. Inferential analyses comprised four discrete steps. First, a series of independent-sample t-tests (for continuous variables: age as well as BDI-II, NEO-FFI-R, MAQ, and STAI-Trait scores) or chi-square tests of contingency (for the categorical variable of sex) assessed the magnitude of between-condition differences in sociodemographic, personality, and health variables at baseline.

Second, we evaluated the time estimates using (a) a one-sample t-test assessing whether, for participants in the Smartphone Present condition, the subjectively estimated duration of the waiting period was significantly different than the actual 13.5-min duration (Hypothesis 1a), (b) a one-sample t-test assessing whether, for participants in the Smartphone-Absent condition, the subjectively estimated duration of the waiting period was significantly different than the actual 13.5-min duration (Hypothesis 2a), and (c) an independent-samples t-test assessing whether there was a significant between-condition difference in subjective time estimation. Note here that if the participant responded to the time perception question by giving a range (e.g., 8-10 mins), we used the midpoint of that range (i.e., 9 mins) as their data point. Seven participants provided ranges and 48 provided exact estimates.

Third, we evaluated whether there were significant increases in anxiety (Hypotheses 1b and 2b) using two 2 (Experimental Condition [Smartphone Present/Smartphone Absent] x 2 (Measurement Point [T1/T2]) repeated-measures ANOVAs, one for each of the outcome variables (STAI-State, STAI-S1/STAI-S2; heart rate, HR1/HR2).

Fourth, we used the rubric presented in Table 1 to code the video-recorded footage and to thereby derive the behavioral data describing the participant's actions during the waiting period. Two independent raters coded the footage. Inter-rater reliability was excellent, Pearson's $r \geq .99$. We timed the duration of each separate coded behavior and then calculated a single sum for each of five major categories: Phone Use (for the Smartphone Present group only), Boredom, Seeking Behavior, Productivity, and Other. Because descriptive analyses of those data suggested the distributions were severely skewed, we used a non-parametric alternative (the Mann-Whitney *U* test) to evaluate Hypothesis 3 (i.e., to test the magnitude of between-group differences in Boredom and Productivity). We evaluated Hypotheses 1c and 2c using descriptive statistics (i.e., we counted the number of participants in the Smartphone Present group who used their phone during the waiting period, and the number of participants in the Smartphone Absent condition who exhibited at least some seeking behavior during the waiting period).

Table 1
Behavioral Coding Key

Category	Behavior(s)
Time to phone (Smartphone Present group only)	How long it takes the participant to start using their phone
Phone use (Smartphone Present group only)	Actively using phone, engaging in behaviors such as: ● Scrolling ● Typing ● Watching videos ● Playing games ● Taking pictures / videos
Boredom	● Swinging on chair ● Lies back on chair / lies down on table ● Fidgeting with pen / paper / HR monitor / fingers ● Looking around the room ● Staring blankly ● Actively exploring the room ● Trying to calculate HR ● Playing with hair
Seeking Behavior (Smartphone Absent group only)	● Approaching where the smartphone is stored
Productivity[3]	● Reading a book/ textbook/ notes ● Making notes ● Doing work on a laptop
Other	● Drinking coffee / other beverages ● Eating ● Listening to music

[3]We acknowledge that individuals can perform productive activities on their smartphones and do not want to imply that we subscribe to the popular myth that smartphone use is always unproductive. However, because we did not monitor what individuals were doing on their smartphones, we cannot differentiate between productive and unproductive smartphone use.

3. Results

3.1. Descriptive Data. Analyses detected no significant between-condition differences in terms of baseline sociodemographic, personality, and health variables (see Table 2). Hence, we concluded that subsequent inferential analyses were unlikely to be confounded by between-condition differences in any of these respects. Because of the high proportion of women in the sample, we assessed for between-sex differences in terms of personality and health variables. Analyses detected no significant differences, *ps* > .092.

Internal consistency reliability estimates (Cronbach's α) based on the current sample's responses on the standardized instruments ranged from acceptable to excellent: BDI-II = .824; STAI-Trait = .882; STAI-State (first administration) = .869; MAQ = .895; NEO-FFI-R Neuroticism = .773; NEO-FFI-R Extraversion = .648.

Regarding depressive symptomatology, most participants ($n = 47$; 85.45%) scored ≤19 on the BDI-II, indicating reports of no more than what is conventionally described as "mild depression" (Beck et al., 1996). Only 2 participants (3.63%; one in each experimental condition) scored in the range conventionally described as "severe depression" (i.e., scores ≥29). Regarding trait anxiety, a one-sample *t*-test suggested that, on average, the current participants scored significantly higher on the STAI-Trait (i.e., were significantly more anxiety-prone) than college students in the standardization sample (Spielberger et al., 1983), $t(54) = 6.46$, $p < .001$. Regarding mobile attachment, no previously published study has reported on norms for the MAQ. However, the MAQ mean and standard deviation in this sample were strikingly similar to those reported by Hodes and colleagues (2020), who also collected data from undergraduate students aged 18–25 years. In both cases, the sample's average score suggested quite strong mobile attachment. Regarding neuroticism, a one-sample *t*-test suggested that, on average, the current participants did not score significantly differently on the NEO Neuroticism subscale from high school students in the standardization sample (McCrae & Costa, 2004), $t(54) = 0.80$, $p = .428$. In contrast, a one-sample *t*-test suggested that, on average, the current participants scored significantly lower on the NEO Extraversion subscale (i.e., were significantly less extroverted) than high school students in the standardization sample, $t(54) = -7.29$, $p < .001$.

Table 2

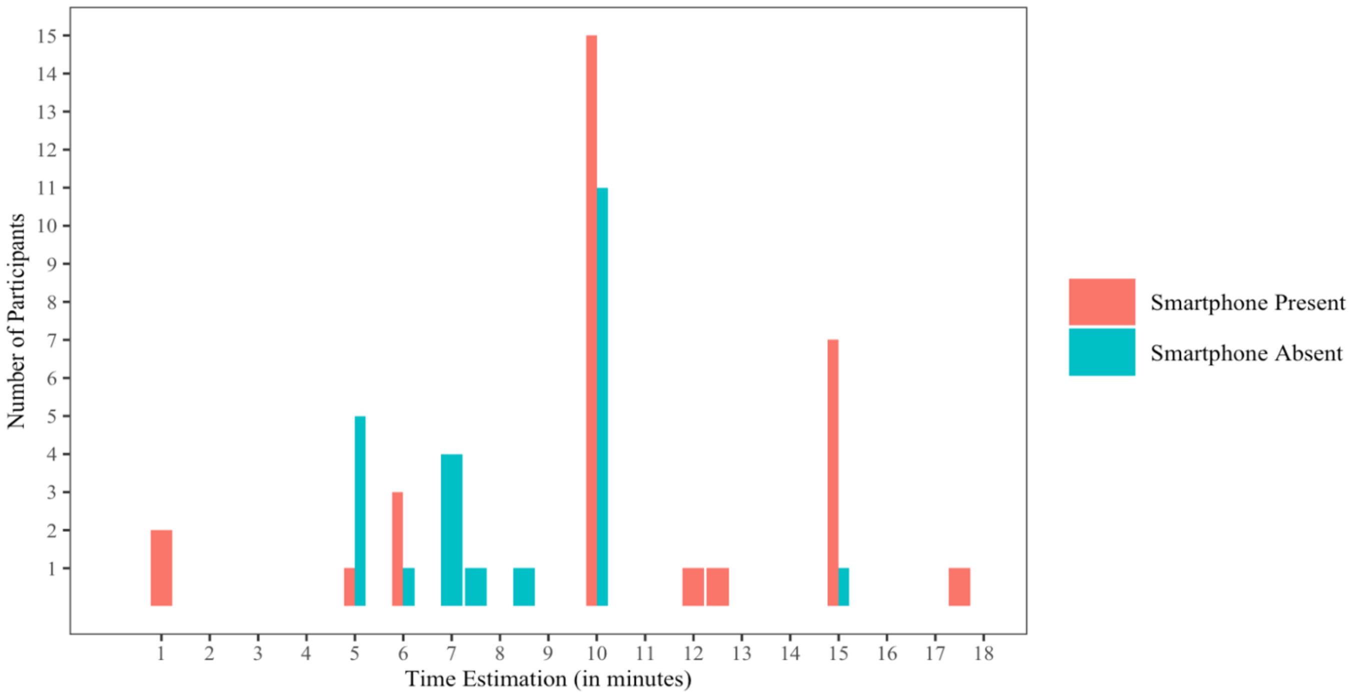
Sample Sociodemographic, Personality, and Health Characteristics (N = 55)

Variable	Condition						
	Smartphone Present (*n* = 31)	Smartphone Absent (*n* = 24)	t / χ^2	*p*	ESE	95% CI LL	95% CI UL
Age (years)			-0.52	.614	.14	-0.74	0.45
M (*SD*)	19.19 (1.01)	19.09 (1.16)					
Range	18–22	18–22					
Sex			0.04	.834	.07	0.01	0.33
Women	24 (77.42%)	20 (83.33%)					
Men	7 (22.58%)	4 (16.67%)					
BDI-II			-0.60	.549	.16	-5.08	2.73
M (*SD*)	14.26 (7.46)	7.48 (1.29)					
Range	4–39	3–9					
MAQ			0.06	.952	-.02	-7.03	7.47
M (SD)	47.03 (11.96)	47.25 (14.16)					
Range	22–63	22–70					
STAI-Trait			-0.17	.864	.05	-5.59	4.71
M (SD)	46.48 (8.70)	46.04 (9.92)					
Range	30–66	26–66					
NEO-FFI-R							
Neuroticism			-1.12	.270	.30	-6.11	1.75
M (SD)	26.81 (7.13)	24.62 (7.23)					
Range	13–39	12–38					
Extraversion			-0.13	.898	.03	-3.18	2.80
M (SD)	26.48 (5.77)	26.29 (5.24)					
Range	14–41	18–36					

Note. ESE = effect size estimate (Cohen's *d* for *t*-tests and Cramer's *V* for chi-squared tests of contingency); CI = confidence interval; LL = lower limit; UL = upper limit; BDI-II = Beck Depression Inventory-Second Edition; MAQ = Mobile Attachment Questionnaire; STAI-Trait = State-Trait Anxiety Inventory-Trait form; NEO-FFI-R = NEO Five-Factor Inventory Revised. All listed *p*-values are two-tailed.

3.2. Time Estimations. Participants in both the Smartphone Present (M = 10.39, SD = 3.97 mins; range = 1–17.50) and Smartphone Absent (M = 8.33, SD = 2.50 mins; range = 5–15) conditions significantly underestimated the duration of the waiting period, $t(30) = 4.37$, $p < .001$, Cohen's d = -1.11, and $t(23) = 10.12$, $p < .001$, Cohen's d = -2.92, respectively. However, because of the greater variation in estimates by participants in the Smartphone Present group (see Figure 3), analyses detected a significant between-group difference in estimated duration, $t(51.14) = 2.34$, $p = .023$, Cohen's d = 0.60.

Figure 3
Frequency of time estimations in the Smartphone Present (n = 31) and Smartphone Absent (n = 24) conditions.



3.3. Self-report and Physiological Measures of Anxiety. Table 3 presents descriptive statistics for the self-report (STAI-State) and physiological (HR) measures of anxiety across the two measurement points. Regarding the STAI-State data, the analysis detected a significant main effect of Measurement Point, $F(1, 53) = 17.06$, $p < .001$, $\eta_p^2 = .24$, but no significant main effect of Experimental Condition, $F(1, 53) = 0.56$, $p = .459$, $\eta_p^2 = .01$, and no significant interaction effect, $F(1, 53) = 1.21$, $p = .276$, $\eta_p^2 = .02$. Regarding the HR data, the analysis detected no significant main effects (Experimental Condition, $F(1, 51)$ =

0.37, p = .544, η_p^2 = .007; Measurement Point, $F(1, 51) = 1.64$, p = .206, η_p^2 = .03) and no significant interaction effect, $F(1, 51) = 0.36$, p = .544, η_p^2 = .007.

Table 3
Self-report and Physiological Measures of Anxiety (N = 55)

	Condition						
	Smartphone	Smartphone				95% CI	
Variable	(n = 31)	(n = 24)	t	p	d	LL	UL
STAI-S_1			-0.31	.759	.09	-5.90	4.33
M (SD)	40.74 (8.76)	39.96 (9.78)					
Range	26–57	22–61					
STAI-S_2			-1.03	.308	.29	-8.28	2.68
M (SD)	37.97 (8.57)	35.17 (10.95)					
Range	20–57	24–61					
HR_1[a]			-0.41	.685	.11	-7.90	5.23
M (SD)	78.00 (11.73	79.33 (11.93)					
Range	56–97	60–111					
HR_2			-0.83	.412	.22	-7.65	3.18
M (SD)	78.52 (10.85)	80.75 (8.75)					
Range	62–100	65–103					

Note. CI = confidence interval; LL = lower limit; UL = upper limit; STAI-S = State-Trait Anxiety Inventory-State form; HR = heart rate.
[a]Based on n = 29: The HR monitor did not record readings for two participants in this group.

3.4. Behavioral Data. Table 4 summarizes the data describing participant behavior during the waiting period. Those in the Smartphone Present condition took an average of 17.03 (*SD* = 76.69) seconds to start using their devices. This statistic is slightly skewed because one participant took approximately 7 minutes to start using their phone. Excluding this individual from the calculation reduces the group average to 3.10 (*SD* = 7.86) seconds. Of note here is that all participants in this group used their smartphones during the waiting period (this piece of data confirms Hypothesis 1c). Twenty-three of the 30 (76.67%) started using their devices before the researcher exited the room, and 16 (53.33%) used their phone continuously throughout the waiting period (i.e., they did not engage in any other activities, and did not put the device down). Ten (33.33%) exhibited signs of boredom (e.g., stared around the room blankly), 3 (10.00%) performed behaviors categorized as “other” (e.g., listening to music or eating), while 2 (6.67%) engaged in productive behaviors (e.g., reading a book). Of note here is that one participant in this group worked on his laptop for most of the waiting period, thus distorting the Productivity average presented in the Table. Excluding this individual from the calculation reduces the group average to 1.03 (*SD* = 5.57) seconds.

All 24 participants in the Smartphone Absent condition exhibited behavioral signs of boredom. Sixteen (66.67%) spent the entire duration of the waiting period showing such signs (e.g., they stared blankly and did not engage in any activities). Only 5 (20.83%) engaged in a productive activity (e.g., they read a book), while 3 (12.5%) performed behaviors categorized as "other" (e.g., they drank coffee). None of the participants showed active seeking behaviors (i.e., they did not move toward the box where their smartphone was stored; this piece of data disconfirms Hypothesis 2c).

Regarding the tests of Hypothesis 3, participants in the Smartphone Absent condition displayed significantly more boredom than those in the Smartphone Present condition, $U = 10.00$, $p < .001$, $\eta^2 = .75$. When including the one outlying piece of Productivity data discussed above, analyses detected no significant between-group differences in that behavior, $U = 309.00$, $p = .128$, $\eta^2 = .04$. However, when that piece of data was removed, participants in the Smartphone Absent condition were significantly more productive than those in the Smartphone Present condition, $U = 285.00$, $p = .041$, $\eta^2 = .08$.

Table 4
Behavioral Coding (N = 54)

	Condition	
Variable	Smartphone Present (n = 30)[a]	Smartphone Absent (n = 24)
Phone Use		
M (*SD*)	726.27 (179.28)	NA
Range	3–810	NA
Boredom		
M (*SD*)	34.67 (93.63)	685.96 (240.37)
Range	0–419	65–810
Productivity		
M (SD)	27.47 (144.88)	90.79 (226.03)
Range	0–794	0–715
Other		
M (SD)	4.93(20.43)	22.25 (85.17)
Range	0–110	0–409

Note. Values presented are in seconds (i.e., 13.5 mins = 810 seconds).
[a]Based on n = 30: One participant did not provide their consent to use their footage.

4. Discussion

This study examined differences in time perception and behavior between two groups of healthy young adults: those who were placed in a 13.5-minute waiting situation where they were allowed to use their smartphone (the Smartphone Present condition), and those who were placed in a similar waiting situation but who were not allowed access to their smartphone (the Smartphone Absent condition). All participants were digital natives (i.e., individuals who have grown up with smartphones; Prensky, 2001). Our main finding was that, contrary to the a priori prediction, participants in both groups (rather than only in the Smartphone Present condition) subjectively underestimated the duration of the waiting period. Below, we discuss how, for each group separately, the findings relating to each of our specific hypotheses might explain that main result, and how our data fit into the context of relevant and recently published literature.

4.1. Smartphone Present Condition. Our analyses confirmed Hypothesis 1, which stated that participants assigned to this condition would (a) subjectively underestimate the duration of the waiting period, (b) show stable anxiety levels from baseline through the end of the waiting period, and (c) actively use their smartphones during that period.

If one assumes that participants in this condition perceived the waiting period as a positive experience (e.g., that they spent the time engaging in pleasurable activities on their smartphone), then this finding is consistent with a prediction derived from the theoretical framework of the time-emotion paradox (i.e., the notion that an individual's emotional state affects how they perceive time; Droit-Volet & Gil, 2009). In other words, for these participants time appeared to pass faster while they were engrossed in those pleasurable activities.

This assumption is supported by three key pieces of evidence. First, none of the participants assigned to this condition accurately guessed the duration of the waiting period (not one even provided an estimate within 30 seconds of the actual time), despite having easy access to their smartphone and/or their watch. This seems to indicate that none of these participants paid particular attention to the elapsing time in the waiting situation.

Second, these participants did not, on average, experience increased subjective or objective anxiety from baseline through the end of the waiting period. In fact, average self-reported anxiety decreased slightly while heart rate remained stable. We speculate that they may have remained calm because they had their smartphones in their possession. This speculation is supported by previous research suggesting that these devices can facilitate relaxation, alleviate boredom and negative moods, and serve as a security blanket in stressful situations (see, e.g., Fullwood et al., 2017; Panova & Lleras, 2016; Rieger et al., 2017; Smetaniuk, 2014).

Third, all participants assigned to this condition used their smartphones during the waiting period. Moreover, a large majority of them used their device for the full duration, and an overwhelming majority started using it even before the researcher left the room. This observation is strikingly similar to that of Brown et al. (2016), who reported that 76% of their participants (N = 126; M_{age} = 18.79, SD = 0.99 years) used their smartphones when left in a 5-min waiting situation with a close friend.

4.2. Smartphone Absent Condition. Our analyses did not confirm Hypothesis 2, which stated that participants assigned to this condition would (a) subjectively overestimate the duration of the waiting period, (b) show increased anxiety levels from baseline through the end of the waiting period, and (c) spend at least some of the waiting time seeking proximity to their device (e.g., walk toward the location where they knew their device was stored). Contrary to the a priori prediction, these participants significantly *underestimated* the duration of the waiting period; in fact, on average their subjective estimate was significantly shorter than that of participants assigned to the Smartphone Present condition. This finding is inconsistent with a prediction derived from the theoretical framework of the time-emotion paradox (i.e., that because being denied access to one's smartphone would be perceived as a negative event, subjective time would slow down until access was restored).

One possible explanation for this inconsistency relates to the fact that the waiting situation did not provoke anxiety in these participants. We predicted that, over the duration of the waiting period, participants assigned to this condition would show significant increases over baseline measures of anxiety because previous studies suggest that confiscating a participant's smartphone and then leaving them to wait alone results in increased self-reported and/or physiological anxiety (see, e.g., Cheever et al., 2014; Clayton et al., 2015; Konok et al., 2017; Panova & Lleras, 2016). However, in this study there were no significant changes in either self-reported state anxiety or heart rate in participants assigned to the Smartphone Absent condition. Hence, we posit that these participants did not experience the kinds of negative emotions (e.g., anxiety) that would have distorted their time perception toward an overestimate of the waiting period's duration.

We also predicted that, during the waiting period, participants assigned to this condition would seek proximity towards their device because basic attachment theory states that a typical response to separation from the attachment figure is seeking to be close to it (Bowlby, 1958). Assessing the application of this theory to smartphones, Konok et al. (2017) reported that digital natives (N = 142; age range = 19–25 years) displayed a significant amount of seeking behavior (i.e., moved toward the cabinet where their phones had been stored) when left alone to wait for 3.5 minutes. In contrast, in our sample none of the participants in this condition exhibited any such seeking behavior. One potential explanation for this discrepancy is that our participants were not as attached to their smartphones as Konok et al.'s participants were to theirs. However, although we used the same measure of smartphone attachment as they did, we cannot make a direct comparison between their data and ours because they do not give details of their MAQ scores and there are no normative data for that instrument. Given that, in our study, participants assigned to this condition had an average MAQ score of 47.25 (SD = 14.16) and the total possible score is 75, there is certainly room for a greater degree of attachment.

An alternative, or contributing, explanation for the discrepancy between our results and those of Konok et al. is that our participants might truly have believed the researcher's warning that their smartphone would interfere with heart-rate monitoring. Researchers in the Konok et al. experiment did not issue such a warning; they merely told participants in their smartphone absent condition that they needed to place their devices in a storage cabinet so that they would not use them for the calculation task that occurred during the experiment.

4.3. Between-group Differences. Our analyses confirmed Hypothesis 3, which stated that participants assigned to the Smartphone Absent condition, relative to those in the Smartphone Present condition, will (a) show behaviors consistent with increased boredom during the waiting period, and (b) engage in productive behaviors during that time. The finding that those in the Smartphone Absent condition showed significantly more behaviors consistent with a feeling of boredom (e.g., staring blankly around the waiting room, swinging on their chair, fidgeting purposelessly) is consistent with previous research suggesting that smartphones alleviate boredom by, for instance, serving as a recreational outlet (see, e.g., Fullwood et al., 2017; Jung, 2014).

Participants in the Smartphone Absent group also spent significantly more time engaging in activities we categorized as productive behaviors (e.g., reading a book, doing academic tasks). This finding is of interest for at least two reasons. First, the fact that these participants were thus occupied offers another potential explanation as to why they, like those in the Smartphone Present condition, underestimated the duration of the waiting period. Second, when taken together with the observation that all participants in the Smartphone Present condition used their devices during the waiting period, this finding reiterates the point that the mere presence of smartphones has the potential to distract and deter individuals from being productive (see, e.g., Froese et al., 2012; Ward et al., 2017).

Another noteworthy between-group difference is that estimates of the 13.5-min waiting period's duration ranged much more widely in the Smartphone Present condition (the shortest estimate was 1 minute, while the longest was 17.5 minutes) than in the Smartphone Absent condition (5–15 minutes). One possible explanation for such a large time estimation range in the former condition, and especially for the very short estimates provided by certain participants (e.g., three estimated <=5 mins), is that these individuals were experiencing what might be characterized as *smartphone flow*. That is to say, rather than simply using their devices to alleviate boredom and flicking between applications, they were fully engaged with a single application in such a way that it allowed them to feel the sensation of time passing quickly. This reasoning is consistent with an observation reported by Lin et al. (2015): They suggested that heavy smartphone users (N = 79; M_{age} = 22.4 years, SD = 2.3; $M_{daily\ use}$ = 4.20 hours, SD = 2.06) underestimated the amount of time they spend on their device because smartphones enable a sense of time distortion.

Conventionally, the concept of *flow* is defined as a state where immersion, involvement, or absorption in an activity is so complete that one loses a sense of time (Csikszentmihalyi, 1990). Although flow is generally associated with enjoyable activities, such as playing music or painting (see, e.g., de Manzano et al., 2010; Lee, 2015), it has also been associated with gaming (see, e.g., Hu et al., 2019; Michailidis et al., 2018). Based on the current data, we suggest that the concept be extended to include smartphone flow—that is, to include the notion one might get fully absorbed into a phone-based activity and thus lose track of time (see also Leung, 2020).

In the existing literature, the experience of flow is strongly associated with personal preferences (e.g., where one person might experience flow while listening to music, another might experience flow while dancing; Bernardi et al., 2018; Chirico et al., 2015). It is likely that the same individual differences will apply to smartphone flow and the applications/activities that will engender or facilitate that state. Unfortunately, because the focus of our data collection was on estimated time duration and on ascertaining whether or not participants in the Smartphone Present condition used their devices, we did not monitor the specific applications or phone-based activities in which these individuals were engaged. If the individual experience of smartphone flow is associated with a particular application/activity, this would be consistent with a growing body of literature suggesting that *what* an individual is doing on their device (and not just *how much* they are using it) is of vital importance when studying smartphone-related behaviors (see, e.g., Boers et al., 2019; Nie et al., 2020).

4.4. Limitations and Directions for Future Research. Inferences from this study's findings must be drawn cautiously and after careful consideration of the following limitations. First, our sample size was relatively small. Data collection had to be cut short because COVID-19 lockdown regulations made it impossible to continue an in-laboratory on-campus experiment under conditions of physical and social distancing. Otherwise stated, our total sample size was based on feasibility and resources rather than an a priori power analysis. A post hoc power analysis using G*Power software (Faul et al., 2009) suggested that for a two-tailed t-test and $\alpha = .05$, the current sample size generated statistical power $(1 - \beta) = .61$. This indicates that our sample size was adequate to detect a medium-sized effect, Cohen's $d = 0.62$, but that the study might have been underpowered to detect smaller effect sizes.

Second, the duration of the waiting situation may not have been long enough to provoke significant frustration and anxiety (perhaps it is telling that no participant asked to leave the room, and none expressed anger at being left alone to wait). Similarly, because the devices and belongings of participants in the Smartphone Absent condition remained in the room with them, they might have been less anxious than had we removed them entirely. Future studies should consider extending the waiting period, removing devices and belongings from the waiting room, and also using more sensitive objective measures of physiological anxiety (e.g., salivary alpha amylase or salivary cortisol; Hellhammer et al., 2009; Nater & Rohleder, 2009).

Third, we did not monitor the applications participants in the Smartphone Present group used while they were waiting. As we note above, what individuals do on their devices is at least as important as how long they do it for. Hence, future studies should add such monitoring to their design in order to ascertain whether certain applications are likely to distort time perception more than others.

4.5. Summary and Conclusions. We examined time perception and behavior in digital natives who were and who were not allowed to use their smartphone during a 13.5-min waiting period. We found that, although participants in both groups underestimated the duration of the waiting period and remained relatively anxiety-free during that time, their behavior while waiting was quite different. Whereas those in the Smartphone Present group tended to only immerse themselves in their devices, those in the Smartphone Absent group did not seek proximity to their devices, which had been placed in a box close to them, and tended to show more behaviors consistent with both boredom and productivity. One implication of these findings is that smartphones are not uniquely distracting, time-distorting, and attractive devices: Even when left without them, young people can (for at least short times) find ways to occupy themselves that are engaging enough to enable errors in time perception (i.e., to make it seem that time has passed by more quickly than it actually has).

This is the first study in the cyberpsychological literature to examine time perception in a standard waiting-room design, and one of the few to measure directly observable behavior via a standardized coding scheme. Although our analyses did not confirm a priori predictions regarding time perception and anxiety in the Smartphone Absent group, they do provide support for the effects of the time-emotion paradox and, to a lesser extent, for existence of a novel concept, smartphone flow, in the Smartphone Present group. Future research should explore conditions under which the effects of the time-emotion paradox might be induced in participants left to wait without their smartphones (e.g., they might place these individuals in highly stressful situations that allow no scope for the implementation of coping strategies via productivity), and conditions under which smartphone flow might be induced more strongly in individuals left to wait with their smartphones.

Chapter Five:
General Discussion

The research described in this thesis aimed to contribute to the body of cyberpsychological literature investigating (a) how smartphone screen time might be measured accurately and reliably, and (b) explanations for why subjective estimates of smartphone screen time tend to be inaccurate and unreliable. These aims were accomplished across two separate studies, each using samples of digital natives. This basic age-based inclusion criterion was set in place because it limited the sample to participants who have grown up with these devices, and are generally more dependent on them, than digital immigrants (Prensky, 2001). The major specific aim of Study 1 was to investigate whether digital natives accurately estimated their screen time. The major specific aim of Study 2 was to investigate whether smartphone-induced time distortion might explain inaccurate subjective estimates of screen time.

In this chapter, I briefly summarize the findings from each study, elaborate on how findings from the two are related to one another, discuss the overall limitations of the research program, and conclude with a comprehensive summary of the contributions this thesis makes to the literature.

Study 1: Summary and conclusions

The primary aim of this study was to assess the reliability of subjectively reported screen time by comparing those estimates with objective measures taken by iOS background applications (i.e., the iPhone's Battery Use Screenshot [BUS; an average of screen time over 10 days] and the iPhone operating system screen time tracker [iOS STT; an average of screen time over 7 days]). A secondary aim was to use the objective screen time data to examine the influence of various environmental, contextual and individual difference factors (e.g., day of the week, COVID-19 lockdown, mobile attachment, and affective status) on smartphone use.

The primary finding was that digital natives did not accurately estimate their screen time. Specifically, the data analyses suggested that, relative to BUS-measured screen time, self-reports significantly underestimated use, and that, relative to iOS STT-measured screen time, self-reports significantly overestimated use. These apparently contradictory findings may be understood as an artifact of the different time periods over which the objective measures were taken: The iOS STT average included one weekend whereas the BUS average included two weekends and, as one of the secondary analyses showed, participants tended to use their smartphones more heavily on weekend days (especially Sundays) than weekdays.

Hence, analyses detected a significant difference between the screen time averages produced by those two objective reports.

Secondary analyses suggested that participants' screen time increased significantly from the measure taken before the COVID-19 lockdown to that taken during the lockdown. This finding confirmed the prediction that screen time can be influenced by external factors. As noted earlier, the external factor need not be of the magnitude of a global public health and sociopolitical crisis; there are significant changes in use depending simply on day of the week.

Secondary analyses also suggested that smartphone attachment completely mediated the relationship between screen time (as measured by the BUS report) and self-reported depressive symptomatology. This result suggests that the amount of use itself may not be directly associated with poor mental health (at least in terms of affective status), and is therefore consistent with previous research reporting that objectively measured smartphone screen time is not directly associated with the severity of depression and anxiety (see, e.g., Rozgonjuk et al., 2018).

Study 2: Summary and conclusions

Because Study 1 showed that there are significant differences between actual (i.e., objectively measured) screen time and self-reported (i.e., subjectively experienced) screen time, Study 2 aimed to investigate whether a particular mechanism (time distortion) might substantially account for those differences. Using a classical waiting room design, the study tested the predictions that individuals will:

(1) when their smartphone is present

- (a) underestimate the duration of a solo waiting period,
- (b) show stable levels of anxiety, and
- (c) use the device

and

(2) when their smartphone is absent

- (a) overestimate the duration of a solo waiting period,
- (b) show increased levels of anxiety, and
- (c) seek proximity toward where the device is stored.

The design and measures taken also allowed a test of the hypothesis that participants in the Smartphone Absent condition would be both more bored and more productive than participants in the Smartphone Present condition.

Analyses confirmed that participants in the Smartphone Present condition (a) significantly underestimated the duration of the 13.5-min waiting period, (b) did not show significant increases in anxiety, and (c) used their smartphones for, in most cases, the entire duration of the waiting period. Contrary to a priori predictions, participants in the Smartphone Absent condition (a) also significantly underestimated the duration of the waiting period, (b) did not show significant increases in anxiety when separated from their devices, and (c) did not seek proximity toward where their smartphones were stored. Between-group analyses suggested that, during the waiting period, participants in the Smartphone Absent condition were significantly more bored and more productive than those in the Smartphone Present condition.

Overall, these results suggest that although smartphone use was apparently so pleasant that it distorted time perception (i.e., made participants feel as though time was passing more quickly than it actually was), smartphone absence was not so aversive as to distort it in the opposite direction.

How Findings from Individual Studies Coalesce

Here, I engage in more detailed discussion of some individual findings, with specific attention to how they, when taken together across the two studies, fit with the existing literature.

Before moving on to that discussion, it is important to emphasize that the research presented in this thesis adds to the body of literature promoting the acceptance of smartphone use as an inevitable and important part of everyday life, and encouraging further research into ways that interaction with the devices affects, and is affected by, individual psychological processes (Panova & Carbonell, 2018). The current research program is therefore explicitly not a part of the body of literature that problematizes and pathologizes heavy smartphone use (see, e.g., Boumosleh & Jaalouk, 2017; Lepp et al., 2014; Stiglic & Viner, 2019) and that advocates for digital detoxes and similarly unrealistic behavioral changes.

Smartphones will not simply disappear from store shelves and from our lives. People are unlikely to voluntarily stop using their devices and, for social, professional, and other reasons, they are equally unlikely to remove themselves from the digital world. In fact, it is likely they will become ever-more dependent on these devices. Hence, research that advances understanding of smartphone use from multiple perspectives is an important contribution to (cyber)psychological science.

Smartphone Attachment

Because the concept of smartphone attachment is borrowed from classic developmental psychology theory, at its core it suggests that individuals have an emotional bond to their smartphones in the same way that infants have an emotional bond to their primary caregivers (see, e.g., Konok et al., 2016; Konok et al., 2017; Meschtscherjakov et al., 2014). In both Study 1 and Study 2, I measured smartphone attachment using the Mobile Attachment Questionnaire (MAQ; Kornok et al., 2017), a 15-item self-report instrument that measures how insecure and/or anxious the respondent feels when separated from the device and how much the device feels like a safe haven and secure base for them. On average, the Study 1 sample (48.61±12.53) reported similar levels of attachment to the Study 2 sample (M = 47.13±12.84).

In Study 1, smartphone attachment mediated the relationship between screen time and depression, suggesting that the amount of use itself may not be directly associated with poor mental health (at least in terms of affective status). In Study 2, MAQ scores were obtained to ensure no significant between-condition (Smartphone Present versus Smartphone Absent) differences in smartphone attachment. This measure was important in helping to interpret participant behavior during the 13.5-min solo waiting period (e.g., perhaps only participants with very high MAQ scores would have sought proximity toward their device when separated from it).

Together, these findings (and particularly those from Study 1) emphasize the centrality of attachment as a vital concept in understanding the human-smartphone interaction. For instance, although screen time and attachment may be associated (see, e.g., Bae, 2017; Konok et al., 2016; Lee et al., 2014), the strength of one’s psychological bond to the device may actually be a bigger factor in explaining smartphone-related behaviors and the impact of the device on everyday activities. Hence, future studies in this field should consider the level and/or type of attachment that individuals have with their smartphones.

Smartphone Flow

As originally conceived, *flow* is defined as a state where immersion, involvement, or absorption in an activity is so complete that one loses a sense of time (Csikszentmihalyi, 1990). Borrowing from this conception, *smartphone flow* could be defined as a state where one might get fully absorbed into a phone-based activity and thus lose track of time. In Study 2, involvement in such a flow state was proposed as a possible explanation for the larger time estimation range in the Smartphone Present than in the Smartphone Absent condition. Recently, Leung (2020) also advocated for the existence of smartphone flow, reporting that such a state might occur when an individual is engaged in either hedonic (entertainment) or eudaemonic (social and information seeking) activities on their device.

Applying the concept to the data from Study 1, one might argue that smartphone flow explains (at least partially) discrepancies between subjective and objective estimates of screen time. Qualitative reports suggested that many individuals were shocked by their BUS and iOS STT reports (i.e., they had not expected to have spent so long on their devices, and were surprised that their self-reports had underestimated their screen time). Hence, these individuals may have been engaging in activities that engendered an experience of smartphone flow. Future studies focused on discrepancies between subjective and objective estimates of screen time, or on ways to reduce screen time, should measure personal propensity toward the activation of smartphone flow states.

Individual Circumstances and Context

One of Study 1's key findings was that smartphone screen time was significantly heavier (a) over the weekend than during the week, and (b) under strict COVID-19 lockdown conditions than pre-lockdown. Previous studies (e.g., Rahmati & Zhong, 2012; Yang et al., 2018) have recommended that such contextual aspects of smartphone use be investigated further. The current Study 1 is one of the first to undertake such an investigation, and the novel findings reported here emphasize the importance of environmental context, broadly defined, when studying individual smartphone-related behavior.

This raises the question of how the laboratory context might have affected the behavior of the Study 2 participants who were assigned to the Smartphone Present condition. Fullwood et al. (2017) reported that their participants self-reported being more likely to use their smartphones when they are home and when they are alone. Hence, on the one hand one might expect that the Smartphone Present condition provided an ideal situation for participants to use their smartphones (i.e., they were alone). On the other hand, the fact that they were in a non-naturalistic laboratory situation may have inhibited their use somewhat. The design of Study 2 did not allow investigation of how much the laboratory context affected smartphone use (i.e., there were no home-based comparative data); future studies might explore this question.

An important aspect of the Study 2 laboratory context is that participants were placed in a solo waiting situation, where they were unaware that they were being watched. Because previous research has suggested that smartphones alleviate anxiety during stressful situations (i.e., they act as a "security blanket"; Panova & Lleras, 2016, p.255; Fullwood et al., 2017; Smetaniuk, 2014), it would be interesting for future research to explore other types of waiting situations that are designed to increase anxiety levels. For example, using a zero-acquaintance laboratory situation where two confederates ignore a third participant while waiting (see, e.g., Albright et al., 1988) would allow assessment of whether participants will turn to their smartphones to buffer the anxiety associated with discomfort at being socially ostracized.

Overall Limitations of the Research Program

The write-up of each empirical study contained within this thesis (i.e., Chapters 3 and 4) concluded with individual discussions of limitations of that particular study's methodological and other limitations. This section, while acknowledging the continued existence of those individual limitations, focuses on broader limitations that cut across the research project generally. These broader limitations should be considered when evaluating the overall significance of the thesis findings and when planning future research based on the current results.

First, the participants in each study were sampled from the same student population. This limited sample diversity places constraints on the generalizability of the findings, and leaves unanswered such questions as whether level of education and occupational status might, for instance, affect smartphone screen time and mobile attachment. Future studies should consider conducting their research across several diverse settings.

Second, the COVID-19 pandemic and consequent government-mandated lockdown had meaningful effects on data collection. For Study 1, I tried to use this crisis to enhance the study (i.e., I investigated the question of how an unprecedented and unexpected public health emergency would influence screen time). This enhancement was successful, as the data from the relatively few students that sent follow-up screen time reports confirmed the a priori predictions. However, the size of this follow-up group was relatively small (participants may have been unresponsive because lockdown conditions may have curbed their motivation or led them to check emails less frequently). Certainly, the pre-lockdown to lockdown comparison would have benefitted from a larger sample.

For Study 2, data collection had to be cut short because of the lockdown regulations; it was impossible to continue an in-laboratory on-campus experiment under conditions of physical and social distancing. Again, this study would have also benefited from a larger sample size. Nonetheless, even though it was statistically underpowered it did produce some interesting, novel, and wholly defensible findings. It would be interesting for future studies in this area to include a control device that is not a smartphone (e.g., a book) to see how or if the results for the Smartphone Absent group might change. Future studies could also attempt to make the waiting situation more stressful (e.g., participants in the Smartphone Absent condition might hear their phone ring) and examine those effects on time perception.

Finally, both Study 1 and Study 2 used the MAQ to assess levels of smartphone attachment. As mentioned earlier, there are no MAQ normative data and hence it was not possible to comment empirically on the overall levels of attachment. Moreover, administering the MAQ to South African undergraduate participants (or to adolescents and emerging adults from similar low- and middle-income countries) may be problematic because the questionnaire includes items asking about individual responses to their sense of safety without the device, leaving their house without their smartphone, and whether they would return to fetch it. In the current studies, participants commented that (a) they would return because they feel unsafe without their smartphone, and (b) their parents would be concerned if they were uncontactable. Hence, in contexts where crime and safety are ever-present concerns there are limitations to administering such questions; it would be worthwhile for future studies to explore cross-national or cross-cultural variability in MAQ responses.

Overall Summary and Conclusions

The research described in this thesis focused on factors (environmental context, individual differences) that can affect subjective estimates of smartphone screen time. Overall, the studies demonstrated that self-reported screen time is an inaccurate representation of actual smartphone use (and that, perhaps, self-report data should not be used in studies investigating correlations between smartphone use and undesirable outcomes [e.g., poor mental health] and that the subjective experience of time while using a smartphone can be influenced by factors internal to and external from the individual user).

Separately, Study 1 concluded that (1) self-reported screen time is relatively inaccurate, with its distribution biased by some extreme estimates; (2) environmental context influences smartphone use; and (3) mobile attachment mediates the association between screen time and depression, implying that it is the user's personal relationship with the device that may account for certain negative mental health outcomes. Study 2 concluded that (1) both smartphone presence and smartphone absence distorted time perception and did not influence anxiety levels; and (2) smartphones are attractive and distracting devices, so much so that when they are present the temptation to use them is too great to withstand. Hence, they can help the user avoid boredom but they also hinder productivity.

Taking these conclusions from the individual studies together, this research added understanding to the human-smartphone interaction by, broadly speaking, emphasizing the importance of measurement, context, attachment, time distortion, and flow. Moreover, the two studies presented in this thesis suggest various new avenues for future research, with recommendations listed at the end of each article. One key concept that should guide future research is to include an analysis of *what* an individual is doing on their smartphone (e.g., what application is being used). The current studies suggest that level of analysis could be a key component in attempts to understand the influence of smartphones on daily life and everyday activities.

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Appendix A:
Sociodemographic Questionnaire

Please answer the following:

Age:

Sex:

Year of study:

Appendix B:

Beck Depression Inventory-Second Edition

Instructions: This questionnaire consists of 21 groups of statements. Please read each group of statements carefully, and then pick out the one statement in each group that best describes the way you have been feeling during the past two weeks, including today. Select the number beside the statement that you have picked. If several statements in the group seem to apply equally well, select the highest number for that group.

1. Sadness

0 I do not feel sad.
1 I feel sad much of the time.
2 I am sad all of the time.
3 I am so sad or unhappy that I can’t stand it.

2. Pessimism

0 I am not discouraged about my future.
1 I feel more discouraged about my future than I used to be.
2 I do not expect things to work out for me.
3 I feel my future is hopeless and will only get worse.

3. Past Failure

0 I do not feel like a failure
1 I have failed more than I should have.
2 As I look back, I see a lot of failures.
3 I feel I am a total failure as a person.

4. Loss of Pleasure

0 I get as much pleasure as I ever did from the things I enjoy.
1 I don’t enjoy things as much as I used to.
2 I get very little pleasure from the things I used to enjoy.
3 I can’t get any pleasure from the things I used to enjoy.

5. Guilty Feelings

0 I don’t feel particularly guilty.
1 I feel guilty over many things I have done or should have done
2 I feel quite guilty most of the time.
3 I feel guilty all of the time.

6. Punishment Feelings

0 I don’t feel I am being punished.
1 I feel I may be punished.
2 I expect to be punished.
3 I feel I am being punished.

7. Self-Dislike

0 I feel the same about myself as ever.
1 I have lost confidence in myself.
2 I am disappointed in myself.
3 I dislike myself.

8. Self-Criticalness

0 I don't criticise or blame myself more than usual.
1 I am more critical of myself than I used to be.
2 I criticise myself for all my faults.
3 I blame myself for everything bad that happens.

9. Suicidal Thoughts or Wishes

0 I don't have any thoughts of killing myself.
1 I have thoughts of killing myself, but I would not carry them out.
2 I would like to kill myself.
3 I would kill myself if I had the chance

10. Crying

0 I don't cry anymore than I used to.
1 I cry more than I used to.
2 I cry over every little thing.
3 I feel like crying, but I can't.

11. Agitation

0 I am no more restless or wound up than usual.

2 I feel more restless or wound up than usual.

2 I am so restless or agitated that it's hard to stay still.

3 I am so restless or agitated that I have to keep moving or doing something.

12. Loss of Interest

0 I have not lost interest in other people or activities.
1 I am less interested in other people or things than before.
2 I have lost most of my interest in other people or things.
3 It's hard to get interested in anything.

13. Indecisiveness

0 I make decisions as well as ever.
1 I find it more difficult to make decisions than usual.
2 I have much greater difficulty in making decisions than I used to.
3 I have trouble making any decisions.

14. Worthlessness

0 I do not feel I am worthless.
1 I don't consider myself as worthwhile and useful as I used to be.
2 I feel more worthless as compared to other people.
3 I feel utterly worthless.

15. Loss of Energy

0 I have as much energy as ever.
1 I have less energy than I used to have.
2 I don't have enough energy to do very much.

3 I don't have enough energy to do anything.

16. Changes in Sleep Pattern

0 I have not experienced any change in my sleeping pattern.

1a I sleep somewhat more than usual.

1b I sleep somewhat less than usual.

2a I sleep a lot more than usual.

2b I sleep a lot less than usual.

3a I sleep most of the day.

3b I wake up 1-2 hours early and can't get back to sleep.

17. Irritability

0 I am no more irritable than usual.
1 I am more irritable than usual.
2 I am much more irritable than usual.
3 I am irritable all the time.

18. Changes in Appetite

0 I have not experienced any changes in my appetite

1a My appetite is somewhat less than usual.

1b My appetite is somewhat more than usual.

2a My appetite is much less than usual.

2b My appetite is much more than usual.

3a I have no appetite at all.

3b I crave food all the time.

19. Concentration Difficulty

0 I can concentrate as well as ever.
1 I can't concentrate as well as usual.
2 It's hard to keep my mind on anything for very long.
3 I find I can't concentrate on anything.

20. Tiredness or Fatigue

0 I am no more tired or fatigued than usual.
1 I get more tired or fatigued more easily than usual.
2 I am too tired or fatigued to do a lot of the things I used to do.
3 I am too tired or fatigued to do most things I used to do.

21. Loss of Interest in Sex

0 I have not noticed any recent change in my interest in sex.
1 I am less interested in sex than I used to be.
2 I am much less interested in sex now.
3 I have lost interest in sex completely.

Appendix C:
State Trait Anxiety Inventory
State form

DIRECTIONS:

A number of statements which people have used to describe themselves are given below. Read each statement and then circle the appropriate number to the right of the statement to indicate how you feel *right* now, that is, *at this moment*. There are no right or wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe your present feelings best.

	NOT AT ALL	SOMEWHAT	MODERATELY SO	VERY MUCH SO
1. I feel calm	1	2	3	4
2. I feel secure	1	2	3	4
3. I am tense	1	2	3	4
4. I feel strained	1	2	3	4
5. I feel at ease	1	2	3	4
6. I feel upset	1	2	3	4
7. I am presently worrying over possible misfortunes	1	2	3	4
8. I feel satisfied	1	2	3	4
9. I feel frightened	1	2	3	4
10. I feel comfortable	1	2	3	4
11. I feel self-confident	1	2	3	4
12. I feel nervous	1	2	3	4
13. I am jittery	1	2	3	4
14. I feel indecisive	1	2	3	4
15. I am relaxed	1	2	3	4
16. I feel content	1	2	3	4
17. I am worried	1	2	3	4
18. I feel confused	1	2	3	4
19. I feel steady	1	2	3	4
20. I feel pleasant	1	2	3	4

STAIP-AD Test Form Y
www.mindgarden.com

Trait form

SELF-EVALUATION QUESTIONNAIRE

STAI Form Y-2

Name____Date__________

DIRECTIONS

A number of statements which people have used to describe themselves are given below. Read each statement and then circle the appropriate number to the right of the statement to indicate how you *generally* feel. There are no right or wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe how you generally feel.

	ALMOST NEVER	SOMETIMES	OFTEN	ALMOST ALWAYS
21. I feel pleasant	1	2	3	4
22. I feel nervous and restless	1	2	3	4
23. I feel satisfied with myself	1	2	3	4
24. I wish I could be as happy as others seem to be	1	2	3	4
25. I feel like a failure	1	2	3	4
26. I feel rested	1	2	3	4
27. I am "calm, cool, and collected"	1	2	3	4
28. I feel that difficulties are piling up so that I cannot overcome them	1	2	3	4
29. I worry too much over something that really doesn't matter	1	2	3	4
30. I am happy	1	2	3	4
31. I have disturbing thoughts	1	2	3	4
32. I lack self-confidence	1	2	3	4
33. I feel secure	1	2	3	4
34. I make decisions easily	1	2	3	4
35. I feel inadequate	1	2	3	4
36. I am content	1	2	3	4
37. Some unimportant thought runs through my mind and bothers me	1	2	3	4
38. I take disappointments so keenly that I can't put them out of my mind	1	2	3	4
39. I am a steady person	1	2	3	4
40. I get in a state of tension or turmoil as I think over my recent concerns and interests	1	2	3	4

STAIP-AD Test Form Y
www.mindgarden.com

Appendix D:
Mobile Attachment Questionnaire

To what extent are the following statements characteristic of you?

1-----------2-----------3-----------4-----------5

1- not at all characteristic of me 5- Very characteristic of me

1. If my phone runs out of battery, I do not feel safe.
2. If I do not have my phone on me, I do not feel safe.
3. If I leave my phone at home, I do not feel safe.
4. If I lost my phone, I would not feel really safe for long.
5. If I am stressed I take out my phone to calm down.
6. If I left my phone at home, I would be willing to go home for it even from a distance (more than 5 min away from home).
7. I am nervous/tense when I leave my phone at home.
8. It does not bother me when I leave my phone at home/it runs out of battery.
9. I am nervous/tense when my phone runs out of battery.
10. If I feel uneasy/tense in company, I take out my phone.
11. In a tense situation I take out my phone.
12. If I am nervous, dealing with my phone does not calm me down.
13. If my phone is in my hand, I feel more confident.
14. I am not more confident/easy-going if I have my phone with me.
15. If my phone is in my hand, I can behave more easily/unreserved.

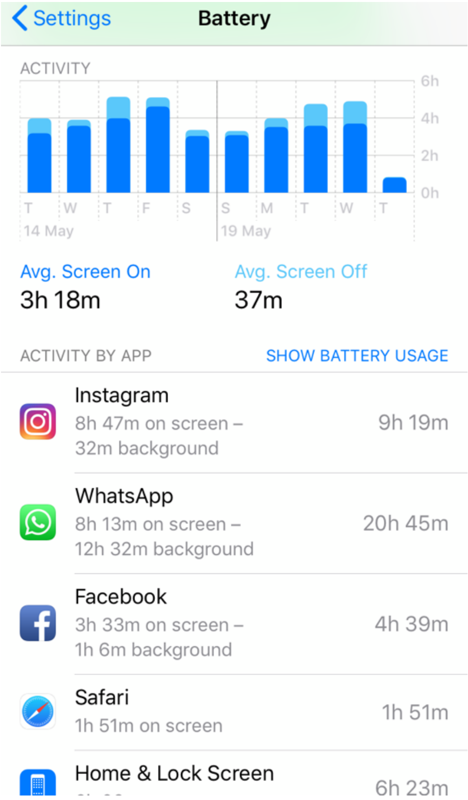
Appendix E:
Instructions for objective screen time report

Please go to the settings function of your phone. Here please select “Screen Time” > Then select the first option which says “(Your name’s) iPhone” > Please change the time frame to the last 7 days > Please take a **clear** screen shot (select lock and home for iPhones 6, 7 and 8 or volume up and lock for iPhone X) of this screen. Please make sure that the 3 most used applications are included in this picture.

Your image should look like:

Please return to the setting page > Scroll down and select “Battery” > Change the time frame to the “last 10 days” > Scroll down to “Battery Usage by app” > Select “show activity” on the left > Please take a **clear** screenshot of these applications.

Your image should look like:



Please email these 2 pictures to screentimeuct2019@gmail.com, with your student number as the subject. Please make sure that the images you send through contain only the information from **your** iPhone. Please **note that if you do not complete these steps, *<u>you will not receive a second</u>* SRPP point from this study** or you will **not be entered into the raffle**. In this email please report if you frequently look at these smartphone usage features. Also, feel free to comment on any outcomes that you were surprised by, all your responses will be kept confidential.

Appendix F:
Study 1 advertisements

SRPP Advertisement (Psychology students only)

Hello there

Do you own an iPhone and are you aged between 18 and 25?

If so you are invited to participate in a new study on technology, behavior patterns and emotions!

This study will require you to fill out an online questionnaire and then to email the researcher. In return for your **complete** participation you will be awarded 2 SRPP points.

Please find the online questionnaire here: https://www.surveymonkey.com/r/behaviour123uct

Please note that to participate you will need to have an iPhone with **iOs 12** or later installed and you will need to be aged **between 18 and 25.** Also this survey will only be open until 17h00 today!

If you have any further queries, please feel free to email me on: HDSLEO001@myuct.ac.za
This study will take no more than **30 minutes** of your time.

Kind regards,
Leora Hodes
MA Research Psychology student
*Please note that you can only participate in this study once

DSA Advertisement (all students)

Hello there

Do you own an iPhone and are you aged between 18 and 25?

If so you are invited to participate in a new study on technology, behavior patterns and emotions!

This study will require you to fill out an online questionnaire and then to email the researcher. In return for your **complete** participation you will be entered into a raffle to win one of three Cavendish vouchers for R250, R500, or R750.

Please note that to participate you will need to have an iPhone with **iOs 12** or later installed and be aged between **18 and 25**.

If you would like to participate, please sign up at:
https://docs.google.com/forms/d/e/1FAIpQLSej8KrJYUvnnH3uL5wa0eTbWqyZgZb3IONCgZYCHSnpKnTbpQ/viewform?usp=sf_link
If you have any further queries, please feel free to email me on: HDSLEO001@myuct.ac.za

This study will take no more than **30 minutes** of your time.

Kind regards,
Leora Hodes
MA Reaserch Psychology student
*Please note that you can only participate in this study once

Appendix G:
Study 1 follow-up advertisement

Hi there

Thank you for your previous participation in my screen time study, and I hope you are keeping safe and healthy! We would truly appreciate it if you could please help us once more - this would take **less than a minute** of your time.

We are currently in a very interesting time for studying smartphone use. Therefore, we would truly appreciate it if you would send through your **screen time data again** by the end of the day. The data will be anonymized and kept strictly confidential. Please read through the consent form below; by replying to this email with your data you will be consenting to participate.

If you do choose to participate, please **follow the steps attached**. Please feel free to email me any questions that you may have.

In return for your complete participation **by the end of the day**, you will be entered into a raffle to win an **R100 Pick n Pay digital voucher.**

Thank you in advance for your assistance!

Leora Hodes

Appendix H:
Study 1 consent form

Consent to Participate in a Research Study

ACSENT Laboratory

University of Cape Town

Dear Student:

Thank you for making time to participate in this study. This study is focused on behaviour patterns and emotions. This study is being performed as part of a Master's degree in the Department of Psychology at the University of Cape Town. Before you agree to take part, please carefully read this page, and email the researcher about any questions you might have.

Study Purpose

The purpose of this study is to look at behavior patterns, emotions and habits in undergraduate students. Specifically, I aim to assess if certain behavior patterns and emotions predict certain behaviors. This research will be used to address a gap in the research regarding these topics.

Study Procedures

If you decide to participate in this study, you will be asked to complete an online questionnaire and email the researcher. The entire testing procedure will take a maximum of 30 minutes and will all take place online.

Possible Risks and Benefits

There are no identified risks for participating in this study. Your responses and scores on all questionnaires will remain confidential under all circumstances, with no one besides the researchers having access to them, and even the researcher will not be able to identify you from your answers.

You will be awarded SRPP points or entered into a raffle to win one of three Cavendish vouchers in return for your complete participation.

Alternatives

You may choose not to participate in this study. Your decision will not affect your relationship with the University of Cape Town or the Department of Psychology in any way, academic or personal.

Voluntary Participation

Participation in this study is completely voluntary. You are free to change your mind and discontinue participation at any time without any effect on your relationship with the University of Cape Town or the Department of Psychology. No-one aside from the researchers will know that you have decided to not participate. Please note that if you decide to cease participation, you will not be awarded the SRPP points or entered into the raffle.

Confidentiality

Information about you collected for this study will be kept completely confidential and anonymous. Your consent forms will be kept in a secure location with access only available to the researcher. The information obtained will not be disclosed to anyone not involved in the research. Any reports or publications about this study will not identify you or any other study participant.

Informed Consent

I have read and understood what is written in this document, and by clicking below, I agree to take part in this study.

Should you have any further questions or concerns, please feel free to contact me, Leora Hodes, at HDSLEO001@myuct.ac.za, or my supervisor, Kevin Thomas, at kevin.thomas@uct.ac.za. If you would like to contact a representative of the Department of Psychology Research Ethics Committee, please telephone or email Ms Rosalind Adams: 021 650 3417 or rosalind.adams@uct.ac.za.

- **I consent to participate**

Appendix I:
Study 1 debriefing form

Debriefing Form
ACSENT Laboratory
University of Cape Town
The difference between actual and self-report screen time

Dear participant:

Thank you for your participation in this study. The aim of this study was to assess if there is a significant difference between actual smartphone screen time and self-report estimations.

Initially you were told that this study was on behavior patterns as I did not want the desire to answer questions in a socially desirable way to influence your scores. Smartphone screen time is considered a normal activity that all individuals take part in, however the understanding of it is less clear. Previous research has used unreliable methods to empirically measure screen time. However advances in the iPhone software, provide a promising platform to address these limitations, enhance our understanding of smartphone screen time, and assess how accurately individuals can predict this.

Remember that your responses will be treated anonymously and confidentially; this means that nobody can find out what responses you gave on any of the questionnaires you completed. Also, please bear in mind that this study is still not complete, so please do not discuss the study aim with friends that may still participate.

Please feel free to ask any further questions you might have by emailing them to me, Leora Hodes HDSLEO001@myuct.ac.za. Please feel free to reach out to me if you feel distressed in any way. Otherwise, please feel free to approach a councillor at Student Wellness. Sessions can be booked at the following link: https://outlook.office365.com/owa/calendar/STUDENTWELLNESSSERVICEPSYCHOLOGICALSERVICES@mscloudtest.uct.ac.za/bookings/

Or else, feel free to contact the UCT Student Careline by dialling 0800 24 25 26 (free from a Telkom line) or SMS 31393 for a call-me-back.

If you have any concerns about the study procedures in general or queries about one's right as a research participant, you may also contact the UCT Department of Psychology ethics committee via Ms Rosalind Adams, rosalind.adams@uct.ac.za

Appendix J:
Study 1 follow-up consent form

Consent to Participate in a Research Study
ACSENT Laboratory
University of Cape Town

Dear Student:

Thank you for making time to participate in this study. This study is focused on smartphone screen time. This study is being performed as part of a Master's degree in the Department of Psychology at the University of Cape Town. Before you agree to take part, please carefully read this consent form, and email the researcher about any questions you might have.

Study Purpose

The purpose of this study is look at smartphone use in undergraduate students. This research will be used to address a gap in the research regarding this topic. You are being invited to participate one last time, because you participated last year.

Study Procedures

If you decide to participate again in this study, you will be asked to send through your screen time and battery use reports. That is the only thing you will be asked to do.

Possible Risks and Benefits

There are no identified risks for participating in this study. Your responses and scores on all questionnaires will remain confidential under all circumstances, with no one besides the researchers having access to them, and even the researcher will not be able to identify you from your answers.
A possible benefit of participating in this study is being made aware of any interesting findings from this research.

Alternatives

You may choose not to participate in this study. Your decision will not affect your relationship with the University of Cape Town or the Department of Psychology in any way, academic or personal.

Voluntary Participation

Participation in this study is completely voluntary. You are free to change your mind and discontinue participation at any time without any effect on your relationship with the University of Cape Town or the Department of Psychology. No-one aside from the researchers will know that you have decided to not participate.

Confidentiality

Information about you collected for this study will be kept completely confidential. The information obtained will not be disclosed to anyone not involved in the research. Any reports or publications about this study will not identify you or any other study participant. Your screen time data will not be able to identify you at all.

Informed Consent

By responding to this email with your data you confirm that you have read and understood what is written in this document and agree to take part in this study.

Should you have any further questions or concerns, please feel free to contact me, Leora Hodes, at HDSLEO001@myuct.ac.za, or my supervisor, Kevin Thomas, at kevin.thomas@uct.ac.za. If you would like to contact a representative of the Department of Psychology, please telephone or email Ms Rosalind Adams: 021 650 3417 or rosalind.adams@uct.ac.za.

Appendix K:
Study 1 follow-up debriefing form

Debriefing Form

ACSENT Laboratory

University of Cape Town

Smartphone use during the nationwide lock down

Dear participant:

Thank you very much for your participation in this study. The aim of this study was to assess if there is a significant increase in smartphone use during the nationwide lock down. Previous research has suggested that smartphone use is dependent on personal demands (i.e, we use our phones more when we have fewer demands on our time), hence this lock down period provided the opportunity to assess this hypothesis.

Remember the fact that your responses will be kept confidential and only averaged data will be reported: this means that nobody can find out what your responses were.

Please feel free to ask any further questions you might have by emailing them to me, Leora Hodes HDSLEO001@myuct.ac.za. If you have any questions or concerns about the study procedures in general, you may also contact the UCT Department of Psychology: Ms Rosalind Adams, rosalind.adams@uct.ac.za.

Appendix L:
NEO Five Factor Inventory Revised

Please respond to the following questions according to the scale

1	2	3	4	5
Strongly disagree	Disagree	Neutral	Agree	Strongly agree

1. I am not a worrier
2. I like to have a lot of people around me
3. I often feel inferior to others
4. I laugh easily
5. When I’m under a great deal of stress, sometimes I feel like I’m going to pieces
6. I don’t consider myself especially “light-hearted”
7. I rarely feel lonely or blue
8. I rarely enjoy talking to people
9. I often feel tense and jittery
10. I like to be where the action is
11. Sometimes I feel completely worthless
12. I usually prefer to do things alone
13. I rarely feel fearful or anxious
14. I often feel as if I’m bursting with energy
15. I often get angry at the way people treat me
16. I am a cheerful, high-spirited person
17. Too often, when things go wrong, I get discouraged and feel like giving up
18. I am not a cheerful optimist
19. I am seldom sad or depressed
20. My life is fast-paced
21. I often feel helpless and want someone else to solve my problems
22. I am a very active person
23. At times I have been so ashamed I just wanted to hide
24. I would rather go my own way than be a leader of others

Appendix M:
Study 2 advertisement

Personality and Mood Study

Dear Participant
You are invited to participate in a novel new study on personality and mood characteristics. You will need to come into the ACSENT laboratory (in the psychology department) for ± **an hour** to fill in some questionnaires and complete a computerized task. You will need to be fitted with a heart rate monitor to complete this study, so please bear this in mind when you pick your outfit for the day, should you choose to participate (i.e. try wear something loose, and do not wear a dress).

You will be awarded a maximum of **2 SRPP points** for completing all the study procedures. The inclusion criteria for this study are: (a) aged between **18 and 25** (You strictly have to be within this age limit, of you are under 18 you cannot sign the consent form); and (b) **no history** of any serious **medical or psychiatric disorders**. Please feel free to email me if you have any questions about this on HDSLEO001@myuct.ac.za.

Please select a participation time slot on the vula tab - can only participate in this study **once.**

Please arrive at the ACSENT sleep laboratory on time, and/or email me if you book a time slot that you cannot attend.

Kind regards,
Leora Hodes
MA Reaserch Psychology student

(*Please not*e: It is generally accepted that the decision to include or exclude individuals from participating in a study depends on the focus, objective, nature of research and context in which the research is conducted. Some research may be focused on a certain individual (such as a person's life history), or a group of individuals who share a specific characteristic (e.g., an identifiable group of asthma sufferers who happen to be all of one sex; a religious order that is restricted to one sex). Other examples include research that is focused on specific cultural traditions or languages, or on one age group (e.g., a study of posture corrections in adolescents). These are regarded as appropriate forms of inclusion and exclusion of individuals or groups in research studies - so long as the selection criteria for those to be included in the research are relevant to answering the research question.)

Appendix N:
Study 2 consent form

Consent to Participate in a Research Study
ACSENT Laboratory
University of Cape Town

Dear Student:
Thank you for making time to participate in this study. This study is focused on personality and mood characteristics. This study is being performed as part of an Master's degree in the Department of Psychology at the University of Cape Town. Before you agree to take part, please carefully read this page, and email the researcher about any questions you might have.

Study Purpose
The purpose of this study is to look at personality characteristics and habits in undergraduate students. Specifically, we aim to assess if certain personality characteristics are related to certain habits and behavior patterns. This research will be used to address a gap in the research regarding these topics.

Study Procedures
If you decide to participate in this study, you will be asked to take part in a laboratory experiment that involves completing questionnaires about your personality characteristics and mood and completing a computer task. You will also be fitted to a heart-rate monitor.

Possible Risks and Benefits
There are no identified risks for participating in this study. Your responses and scores on all questionnaires will remain confidential under all circumstances, with no one besides the researchers having access to them, and even the researcher will not be able to identify you from your answers.
You will be awarded 2 SRPP points for your complete participation.

Alternatives
You may choose not to participate in this study. Your decision will not affect your relationship with the University of Cape Town or the Department of Psychology in any way, academic or personal.

Voluntary Participation

Participation in this study is completely voluntary. You are free to change your mind and discontinue participation at any time without any effect on your relationship with the University of Cape Town or the Department of Psychology. No-one aside from the researchers will know that you have decided to not participate. Please note that if you decide to cease participation, you will not receive the SRPP points.

Confidentiality

Information about you collected for this study will be kept completely confidential and anonymous. Your consent forms will be kept in a secure location with access only available to the researcher. The information obtained will not be disclosed to anyone not involved in the research. Any reports or publications about this study will not identify you or any other study participant. Your test scores will not be able to identify you at all.

Informed Consent

I, __________________________, have read and understood what is written in this document, and by signing here, I agree to take part in this study.

Participant's signature: ___________________________________ *Date:* ____________

Name and student number of Participant (for SRPP purposes, Psychology students only):

____

Course code and title (for which you would like these points, Psychology students only):

____

Should you have any further questions or concerns, please feel free to contact me, Leora Hodes, at HDSLEO001@myuct.ac.za, or my supervisor, Kevin Thomas, at kevin.thomas@uct.ac.za. If you would like to contact a representative of the Department of Psychology Research Ethics Committee, please telephone or email Ms Rosalind Adams: 021 650 3417 or rosalind.adams@uct.ac.za.

Appendix O:
Consent to use video footage

I _______________(your name), allow the researcher (Leora Hodes), to use my video footage in her research.

I acknowledge that this footage will not be used to personally identify me and only the researcher will have access to it.

Signature:
Date:

Appendix P:
Study 2 debriefing form

Experiment Debriefing form
ACSENT Laboratory

University of Cape Town

Screen Time and Time Distortion: Does Smartphone Use influence time perception?

Dear participant:

Thank you for your participation in this study. The aim of this study was to assess if there is a significant difference in time perception when waiting with and without one's smartphone.

Initially you were told that this study was on personality characteristics as I needed to deceive you in order to ensure you did not behave any differently. In this experiment you were videoed to see your behavioural responses to having your smartphone present or absent. You are entitled to say if you would not like me to use this footage.

Remember the fact that your responses will be treated anonymously, and confidentially; this means that nobody can find out what responses you gave on any of the questionnaires you completed.

Please feel free to ask any further questions you might have by emailing them to me, Leora Hodes HDSLEO001@myuct.ac.za. Please feel free to reach out to me if you feel distressed in any way. Otherwise, please feel free to approach a councillor at Student Wellness. Sessions can be booked at the following link: https://outlook.office365.com/owa/calendar/STUDENTWELLNESSSERVICEPSYCHOLOGICALSERVICES@mscloudtest.uct.ac.za/bookings/

Or else, feel free to contact the UCT Student Careline by dialling 0800 24 25 26 (free from a Telkom line) or SMS 31393 for a call-me-back.

If you have any concerns about the study procedures in general or queries about one's right as a research participant, you may also contact the UCT Department of Psychology ethics committee via Ms Rosalind Adams, rosalind.adams@uct.ac.za